Manufacturing Decline, Housing Booms, and Non-Employment

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Abstract

We assess the extent to which manufacturing decline and housing booms contributed to changes in U.S. non-employment during the 2000s. Using a local labor market design, we estimate that manufacturing decline significantly increased non-employment during 2000-2007, while local housing booms decreased non-employment by roughly the same magnitude. The effects of manufacturing decline persist through 2011, but we find no persistent non-employment effects of local housing booms, most plausibly because housing booms are associated with subsequent busts of similar magnitude. We also find that housing booms significantly reduce the likelihood that displaced manufacturing workers remain non-employed, suggesting that housing booms "mask" non-employment growth that would have otherwise occurred earlier in the absence of the booms. Applying our estimates to the national labor market, we find that hosing booms reduced non-employment growth by roughly 30 percent during 2000-2007 and that roughly 40 percent of the aggregate increase in non-employment during 2000-2011 can be attributed to manufacturing decline. Collectively, our results suggest that much of the non-employment growth during the 2000s can be attributed to manufacturing decline and these effects would have appeared in aggregate statistics earlier had it not been for the large, temporary increases in housing demand. (J21, E24, E32)

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1 Introduction

The share of the population employed has fallen sharply since the peak of the last business cycle in 2007, with especially pronounced changes for those with less skill. For example, between 2007 and 2011 non-employment rates for men aged 21-55 with four year college degrees went from 6.5 percent to 10 percent, and surged from 17 percent to 25 percent for men aged 21-55 without a four year college degree. What accounts for these changes? A number of recent papers have examined changes in employment outcomes since 2007, studying the role of factors like de-leveraging associated with falling housing prices (Mian and Sufi 2012), policy uncertainty (Bloom et al. 2012), unemployment benefit extension (Rothstein 2012), the expansion of government transfer programs (Mulligan 2012), and spatial and industry mismatch (Sahin et al. 2012). Yet, non-employment rates were actually increasing *throughout* the 2000s, long before the start of the 2008-2010 recession.[2] Focusing on the two business cycle peaks before 2007, non-employment rates for prime aged men rose by 1 percentage point between 1989 and 1999, and by an additional 2.5 percentage points between 1999 and 2007 – both massive increases, involving millions of workers.[3] These trends suggest that current patterns of non-employment may be partly attributable to forces that predate 2007, and that understanding current non-employment patterns requires a focus on a period spanning, at least, all of the 2000s.

This paper studies how non-employment during the entire 2000s was affected by two large changes in the national economy during the 2000s: the continuing decline of the manufacturing sector, and the national boom and bust in the housing market. We study both the separate effects of these two phenomena and how they interacted to affect non-employment for different population subgroups between 2000 to 2007 and over the entire 2000-2011 period. We focus on manufacturing decline and the housing boom/bust partly because of how large these phenomena were. In the two decades prior to 1999, U.S. manufacturing employment fell from roughly 18.2 million to 17.4 million. However, in the relatively short time between 1999 and 2007, U.S. manufacturing employment fell by an *additional 4 million jobs*. The decline continued through the 2007-2011 period, with an additional 2 million manufacturing jobs lost.[4] Changes in the housing market were equally dramatic: between 1997 and 2007, after decades of being relatively flat, housing prices surged by about 37

[2] See Moffit (2012) for a discussion of this phenomenon.

[3] All numbers in this section come from the authors' calculations using the Current Population Survey (CPS). The sample was restricted to men between the ages of 21 and 55 (inclusive).

[4] Data for changes in manufacturing employment are from the Bureau of Economic Analysis.

percent, before entirely collapsing over a couple of years.[5]

Beyond the scale of these changes, employment in manufacturing and in activities affected by changes in the housing market have historically been particularly important for less skilled persons - the sub-group experiencing the largest changes in non-employment since 2000. Figures 1a and 1b use data from the Current Population Survey (CPS) to plot the share among *all* persons, whether working or not, of men and women aged 21-55 (henceforth, "prime-aged") without a four year college degree (henceforth, "non-college") working in manufacturing and in construction. Increased housing demand should stimulate changes in construction activity and may also change demand for local labor services as household wealth increases from changes in housing prices. The patterns in Figure 1 for construction employment thus likely represent a lower bound on the total employment changes associated changes in housing demand. Figure 1a shows that fully 37 percent of all non-college men worked in one or the other of these sectors in 1977, and more than 20 percent of all such men continue to do so in 2011. Manufacturing employment for these men has declined sharply over time, falling from 27 percent in 1977 to 14 percent today. Construction employment among non-college men was fairly constant at about 10 percent between 1977 and 1997, then surged during the housing boom to 15 percent, before collapsing with the housing bust after 2007. Although lower than rates for non-college men, employment in manufacturing among non-college women has traditionally been been significant. These rates declined substantially during the early 2000s. Very few non-college women have historically worked in construction, a pattern which was unchanged over the course of the boom and bust in housing.

Figure 1 offers suggestive hints that manufacturing decline and changes in the housing market may have played an important role in the evolution of non-employment since 2000. For example, the patterns suggest that between 2000 and 2007 the roughly five percentage point decline in the share of men working in manufacturing was roughly offset by the roughly five percentage point increase in the share of men working in construction. After 2007, the share of men working in either manufacturing or construction fell sharply as manufacturing continued to decline and the construction share reverted to is pre-housing boom level. Second, changes in construction employment during the 2000-2007 period did not offset the decline in the manufacturing share for non-college women. This result suggests that if the housing boom lifted the employment prospects of

[5] There are two bodies of literature studying why these phenomena occurred – something that is not the focus of our paper. For manufacturing decline, see Autor et. al (2012) for analysis of the role of import competition from China in explaining recent U.S. manufacturing declines. For housing, see Mayer (2011) and the cites therein for a discussion of why house prices changed during the early 2000s and why they reverted during the late 2000s.

non-college women, it would likely be through sectors other than construction.

Moving beyond suggestive time series evidence, this paper formally studies the effect of manufacturing decline and the temporary boom and bust in housing on non-employment using a local labor market strategy which exploits variation across metropolitan statistical areas (MSAs) during the 2000s in both the size of the manufacturing decline and in the size of the local housing demand change. Following Bartik (1991) and Blanchard and Katz (1992), we construct a measure of the predicted change in manufacturing demand in an MSA given by the interaction between an MSA's initial industry mix and national changes in industry employment within narrowly-defined manufacturing industries.[6] The logic of this "Bartik" measure is that the national decline in the manufacturing sector differentially impacted MSAs because of *pre-existing* differences in the level and composition of manufacturing in the area and the fact that specific manufacturing industries experienced different trends over time. This measure is therefore likely to be systematically unrelated to any change specific to the MSA – such as MSA-specific labor supply shocks during the 2000s – that may also affect labor market outcomes. Reassuringly, we find that the Bartik measure of predicted local manufacturing change very strongly predicts *actual* changes in MSA manufacturing employment from 2000-2007, suggesting that the measure indeed captures changes in local manufacturing activity in our analysis.

Housing price changes were the most dramatic manifestation of housing demand changes over the 2000s, but there were also almost surely changes in the quantity (or quality) of housing which are less readily observed. Using a simple demand/supply framework, we derive a measure of changes in local housing demand that, in principle, captures both the price and quantity effect. Our estimated housing demand measure is a function of the observed price change in the local area and the local housing demand and housing supply elasticities. There is growing consensus that the large temporary changes in housing prices during the 2000s stemmed from factors like the expansion of credit to sub-prime borrowers, low interest rates, the rise of securitization instruments for mortgages in the financial sector and investor speculative activity, rather than from changes in household income, population, or construction costs (Mayer 2011; Sinai 2012). This suggests that most of the observed changes in housing demand during the 2000s may be independent of changes in traditional latent factors that also directly affect MSA labor market outcomes. Nonetheless, in addition to our main OLS results, we also present Two Stage Least Squares (TSLS) results where we instrument for the change

[6] Bound and Holzer (1993) employ a very similar method in their work showing a relatively sharp negative relationship between sectoral declines in manufacturing during the 1970s and 1980s and wage and employment outcomes for men.

in estimated housing demand. To do this, we introduce a new instrumental variable that exploits structural breaks in the evolution in housing prices in an MSA, arguing that these "sharp", or relatively discrete, jumps in housing prices are exogenous with respect to any changes in latent confounds, like labor supply shocks or changes in labor demand, which likely evolve smoothly over time.[7] Across all specifications, we find broadly similar effects for estimated housing demand changes in both the OLS and TSLS specifications, suggesting that variation in MSA housing prices between 2000 and 2007 was not substantially confounded by unobserved labor supply shifts or other unobserved changes in labor demand.

We find that predicted 2000-2007 manufacturing decline in an MSA increased non-employment, lowered wages, and reduced MSA population. The effects for non-employment and wages were substantial: a one standard deviation increase in the predicted decline in manufacturing in an MSA increased the overall non-employment rate for prime-aged individuals in the MSA by 0.7 percentage points and reduced wages by 1.1 percentage points during the 2000-2007 period.[8] The estimated effects on non-employment and wages were largest for non-college workers. Additionally, we find that positive shocks to housing demand in an MSA during 2000-2007 decreased non-employment and increased wages. In particular, a one standard deviation increase in housing demand within an MSA lowered the non-employment rate by 0.8 percentage points and increased wages by 1.8 percentage points for all prime age workers. The effect of the housing demand change was largest for non-college men and smallest for college women. Roughly 80 percent of the decline in non-employment for non-college men in response to the local housing demand increase was the result of increased construction employment. Non-college women also experienced a large decrease in non-employment in response to the housing demand increase during the early 2000s, but virtually none of it resulted from increased construction employment. Positive housing demand changes decreased non-employment of non-college women mainly through greater employment in the retail and service sectors.

Interestingly, over the *entire* 2000-2011 period, we find that the effect of a change in housing demand in an MSA during the housing boom period was quite small. This results from the fact that almost all of the MSAs experiencing large house price increases from 2000-20007 experienced equally large reductions in housing prices

[7] Our approach is similar in spirit to recent work which uses variation arising from structural breaks to identify effects of interest, such as the work by Card, Mas, and Rothstein (2008) on racial tipping.

[8] Though substantial, the effect of declining manufacturing employment is far less than one-for-one. For every one percentage point decline in the manufacturing employment share (out of the total population), the non-employment rate increases by 0.4 percentage points. As we show below, this number is consistent with the medium run re-employment rate of displaced manufacturing workers from the Displaced Worker Survey (DWS).

from 2007-2011. The housing boom lifted local labor markets while the housing bust depressed them. These results contrast sharply with those for manufacturing decline, for which we estimate consistently large effects over the longer term.

According to our estimates, roughly 40 percent of the increase in non-employment from 2000-2011 was attributable to declining manufacturing.[9] We show that a large portion of the manufacturing effect on non-employment was due to an increase in being out of the labor force rather than an increase in unemployment. Additionally, we find that most of our non-employment effect occurred prior to recent recession; manufacturing decline post-2007 accounted for only 18 percent of the increase in non-employment during the 2007-2011 period. We find that between 2000 and 2007 the U.S. housing boom reduced the non-employment rate by roughly 1 percentage point. Over the 2000-2011 period, the housing boom explains very little of the increase in non-employment because the housing bust merely undid the employment gains from the preceding housing boom.

Our results suggest that the temporary housing price boom during 2000-2007 "masked" some of the adverse labor market effects of the sectoral decline in manufacturing, in the sense that the large non-employment effects caused by that sectoral decline would have otherwise been evident in the pre-recessionary period of 2000-2007. We document three distinct dimensions to this masking. First, there was significant "cross-MSA" masking: many of the places experiencing large declines in manufacturing employment were different from the places experiencing large, positive housing demand changes. Second, there was "cross-individual" masking, in the sense that within places experiencing significant manufacturing decline as well as large increases in housing demand, the effects of these sectoral changes affected different population sub-groups. For example, older workers were more adversely affected by the decline in manufacturing than were younger workers, while younger workers were more likely to experience increased construction employment following increases in housing demand. Finally, we document significant "within-individual" masking. Using detailed data from the Displaced Workers Survey (DWS) we find that workers displaced from the manufacturing sectors during 2000-2007 were much less likely to end up in non-employment if they lived in a MSA in which housing demand increased sharply from 2000-2007.[10]

[9] As we discuss below, our results are not substantially affected by accounting for the estimated migration response to the manufacturing and housing shocks when applying our local labor market estimates to a national context. We argue that, if anything, allowing for a migration response as well as other relevant general equilibrium considerations tends to *increase* the estimated importance of declining manufacturing in accounted for observed changed in non-employment.

[10] We are grateful to Hank Farber for suggesting this analysis of the DWS.

Besides providing new evidence about the effects of arguably two of the largest market-wide phenomena of the past 20 years, our results speak to the ongoing debate about whether there is a structural component to the current high levels of non-employment in the U.S. The finding that the housing boom through 2007 masked systematically worsening labor market conditions from manufacturing decline suggests that changes in employment since 2007, the focus of much recent work, may overestimate the cyclical component in the U.S. labor market. Similarly, the result that manufacturing decline accounts, by itself, for 40 percent of the increase in non-employment since 2000 suggests an important explanatory role for factors that are not purely cyclical. It is worth emphasizing that our results do *not* imply that cyclical forces do not matter importantly for high levels of non-employment. Indeed, the non-employment growth not accounted for by our estimates may be due to cyclical forces, labor supply responses to changing government policies, or to other structural forces such as mismatch. One additional point worth stressing is that the short-to-medium run effects we estimate for manufacturing decline may be ameliorated over the longer term as workers make adjustments like acquiring more formal human capital, training for new occupations, or moving to new locations.

The remainder of the paper proceeds as follows. We present the empirical framework in Section 2. Section 3 discusses the data. Sections 4 presents our main empirical results while Section 5 shows that those results are robust to instrumenting for local changes in housing demand. In Section 6 we outline a simple model that extends the classic Roy framework to include non-employment in the presence of different sectoral shocks. The model provides intuition about the different types of offsetting, or "masking" that might arise from sectoral shocks of different signs. In Section 7, we present results on "masking", including results from micro data showing the degree to which individuals displaced in manufacturing were better able to find employment because of a booming housing market. In that same section, we also provide our summary counterfactual results of how labor market outcomes would have evolved since 2000 had the sector changes in manufacturing and housing had not occurred. We conclude in Section 8.

2 Empirical Model

The empirical analysis focuses on comparisons across metropolitan statistical areas (MSAs), which we denote k. We assume that changes in labor market outcomes in a given MSA, ΔL_k, are determined, in part, by labor demand changes arising in three sectors: manufacturing (ΔD_k^M), the housing market (ΔD_k^H), and "other" sectors (ΔD_k^O). Labor market outcomes are also affected by labor supply elasticities or other labor supply changes, which we denote $\Delta\theta_k$. Observed changes in labor market outcomes in a given MSA can thus be written as the general function:

$$\Delta L_k = f\left(\Delta D_k^M, \Delta D_k^H, \Delta D_k^O, \Delta\theta_k\right). \tag{1}$$

We seek to estimate the effects of changes in the manufacturing sector ($d\Delta L_k / d\Delta D_k^M$) and in housing demand ($d\Delta L_k / d\Delta D_k^H$).

To empirically implement (1) we construct measures for changes in local manufacturing demand and local housing demand. For local manufacturing demand changes, we use a variant of the widely-used measures that follow Bartik (1991).[11] Specifically, we measure sectoral shifts in local manufacturing using:

$$\widehat{\Delta D_k^M} = \sum_{j=1}^{J} \varphi_{k,j,2000}\left(\upsilon_{-k,j,2007} - \upsilon_{-k,j,2000}\right)$$

where $\varphi_{k,j,2000}$ is the share of relevant population employed in industry j in city k in the year 2000 and $\upsilon_{-k,j,t}$ is the national employment of industry j excluding city k in year t. The set of industries in J includes all 3-digit industries in manufacturing sector. Effectively, this measure presumes that a *national* decline in the manufacturing sector differentially affects local manufacturing based on the importance and distribution of manufacturing employment in the local market at some time preceding the change.

To derive a measure for change in housing demand, we assume that the log of housing demand and housing supply in a market are given by:

$$\begin{aligned} \log(H_k^D) &= \omega_k^D - \eta_k^D \log(P_k) \\ \log(H_k^S) &= \omega_k^S + \eta_k^S \log(P_k). \end{aligned} \tag{2}$$

In (2), ω_k^D and ω_k^S are, respectively, factors that affect the demand and supply of housing at a given local housing price, P_k, while η_k^D and η_k^S are the price elasticities of housing demand and supply, respectively. Log differentiating the equilibrium condition $H_k^D(P_k) = H_k^S(P_k)$ and letting Δ denote log differences, the effect of

[11] See Blanchard and Katz (1992), Autor and Duggan (2003), Luttmer (2005), and Notowidigdo (2012) for other examples of work using variants of this "Bartik" measure.

a shock to housing demand can be expressed as:

$$\Delta\omega_k^D = \eta_k^D \Delta P + \Delta H^S. \tag{3}$$

In general, a change in housing demand produces two effects: a change in the equilibrium housing price and a change in the amount of housing units supplied in the market. Both the effect on house prices and the change in the housing stock can affect local labor market outcomes, perhaps to different degrees.[12] In particular, house price changes affect household wealth or liquidity and thus households' demand for goods and services produced in the local market (Mian and Sufi, 2012). Changes in the amount (or quality) of housing necessarily involves construction activity such as demolition, renovation, home improvements, or new construction. Our analysis does not disentangle the separate effects of household wealth and construction channels, but rather focuses on the combined effect of changes in housing demand.

Recalling that η_k^S in equation (2) is simply $\Delta H^S/\Delta P_k$, the effect of a *ceteris paribus* shock to housing demand may be written:

$$\Delta\omega_k^D = \eta_k^D \Delta P + \Delta H^S = (\eta_k^D + \eta_k^S)\Delta P_k. \tag{4}$$

Expression (4) suggests that, *so long as there are no shocks to housing supply*, a natural empirical measure of a housing demand change is $\widehat{\Delta\omega_k^D}$ - where $\widehat{\Delta\omega_k^D}$ is computed using observed changes in local house price, existing estimates of the local housing supply elasticity in each MSA, and estimates from the literature of the housing demand elasticity. In principle, our measure of the housing demand change ($\widehat{\Delta\omega_k^D}$) captures *both* the price-related "wealth channel" (via $\eta_k^D \Delta P$) and the resulting quantity-related "construction channel" (via ΔH^S). The intuition for the housing demand change measure is as follows: if two MSAs have the same change in house prices and the same housing demand elasticity, but one has a much larger housing supply elasticity, our measure assigns a larger estimated housing demand change to the more elastic MSA since a larger change in demand would be necessary to generate a similar price change.

[12] In the Online Appendix, we show that if the effect of housing prices and housing quantities on labor market outcomes are different in magnitude, then we will estimate a weighted average of the two effects, with the weights based on the price elasticities of housing demand and supply.

We create an empirical specification based on equation (1) given by:

$$\Delta L_k = \beta_0 + \beta_1 \widehat{\Delta D_k^M} + \beta_2 \widehat{\Delta\omega_k^D} + \alpha X_k + \Delta D_k^O + \Delta\theta_k + \epsilon_k, \tag{5}$$

where X_k is a vector of observable controls, ΔD_k^O and $\Delta\theta_k$ are unobserved, and ϵ_k is a mean-zero regression error. The parameters β_1 and β_2 measure, respectively, the direct effect of a predicted change in local manufacturing and of a change in to local housing demand, holding the other variable constant. The *total* effect of either $\widehat{\Delta D_k^M}$ or $\widehat{\Delta\omega_k^D}$ consists of the sum of their relevant direct effect, plus any indirect effect operating through the effect of the variable in question on the other measure. We assume that changes in local housing demand do not affect local manufacturing activity predicted off national trends in manufacturing. The total effect of estimated housing demand changes on labor market outcomes, or $d\Delta L_k/d\widehat{\Delta\omega_k^D}$, is thus simply β_2. By contrast, standard spatial equilibrium models, such as (Roback 1982), suggest that, besides changes in local manufacturing, housing prices are affected by changes in local labor supply and by changes in *any* local sector. It therefore follows that our estimate of local housing demand changes may be written as:

$$\widehat{\Delta\omega_k^D} = \delta_0 + \delta_1 \widehat{\Delta D_k^M} + f(Z_k) + \Delta D_k^O + \gamma X_k + \Delta\theta_k + \nu_k, \tag{6}$$

where ν_k is an error term, and Z_k represents factors specific to the housing sector such as changes in mortgage-lending technology, loan under-writing standards, or securitization of mortgages that affect housing demand. Equations (5) and (6) jointly imply that the total effect of a manufacturing shock on labor market outcomes is therefore $d\Delta L_k/d\widehat{\Delta D_k^M} = \beta_1 + \delta_1\beta_2$.

We report estimates of the total effect of changes in manufacturing and housing demand based on estimation of the parameters β_1, β_2 and δ_1. Our baseline estimates of these parameters are from a two-step OLS procedure. We first estimate (6) and retain the estimate δ_1. We then estimate (5) to recover estimates of β_1 and β_2. This regression consistently estimates the two direct effects so long as $\widehat{\Delta D_k^M}$ and $\widehat{\Delta\omega_k^D}$ are unrelated to any unobserved changes in other sectors or to local labor supply. One of the key arguments justifying the use of "Bartik" measures in the literature is precisely that a measure like $\widehat{\Delta D_k^M}$ is likely to be orthogonal to changes in local confounds because it is predicted off of national changes in manufacturing. By contrast, as (5) shows, estimated local housing demand changes may depend on changes in unobservable factors that also affect labor market outcomes. In addition, latent housing supply changes would introduce error into the housing demand measure.

To address both the potential endogeneity of $\widehat{\Delta\omega_k^D}$ in (6) and to account for any attenuation bias arising from measurement error in the measure caused by unobserved housing supply changes, we present Two Stage Least Squares (TSLS) estimates in addition to the baseline OLS results. In the TSLS models, we instrument for $\widehat{\Delta\omega_k^D}$ in the second step of the two-step estimation procedure. The instrumental variable Z_k we use is a measure of the degree to which the *quarterly* time series of housing prices in an MSA exhibited a sharply discontinuous structural break at some point between 2003 and 2005, rather than evolve smoothly over time. As we show below, both the presence and size of these structural breaks strongly predicts the estimated change in housing demand over the eight years, $\widehat{\Delta\omega_k^D}$. As most standard models assume, sectoral shocks or labor supply changes get smoothly incorporated into housing price changes. However, other housing demand shocks, such as those that might arise from a change in the lending standards or a housing bubble, can affect housing prices either smoothly or discontinuously. If these structural breaks are orthogonal to the effect of other latent confounds, they are valid instruments for the change in housing prices in TSLS estimation of equation (4) and (5). We discuss our instrument at greater length in Section 5.

Throughout the analysis, standard errors are clustered by state, and we compute standard errors on $d\Delta L_k/d\widehat{\Delta D_k^M}$ using standard methods for two-step estimators (Greene 2000).[13] The analysis is conducted in first differences and thus accounts for time-invariant differences across MSAs. In most specifications, the X vector includes controls for the share of employed workers with a college degree, the share of women in the labor force, and the MSA population. Below, we discuss the data used in the analysis in greater detail.

3 Data

The empirical analysis spans 2000-2011, which covers both the 2000-2007 housing boom and the 2007-2011 housing bust. Our analysis begins in 2000 because reliable data on a representative sample of MSAs are only available in the Census before 2000. We create a panel of MSAs using data from the 2000 Census and from various years of the American Community Survey (ACS) individual-level and household-level extracts from

[13] We obtain very similar standard errors when we bootstrap the standard errors across the two-step procedure, re-sampling states with replacement. Note that the OLS estimates of the two-step model are analogous to estimating a Seemingly Unrelated Regressions (SUR) model on the two-equation system.

the Integrated Public Use Microsamples (IPUMS) database (Ruggles et al., 2004). Restricting attention to persons living in metropolitan areas, we compute mean wages, non-employment shares, employment shares in various occupations, and total population in each MSA. In 2000, these means are from the 2000 Census. For the 2007 numbers, we pool the ACS data from 2005 to 2007 to increase the precision of the MSA estimates. Similarly, we pool the 2009-2011 ACS for the 2011 numbers. Because of the large sample sizes, the various means can be reliably estimated for separate sex×education groups. The primary sample consists of non-institutionalized persons aged 21-55. Much of the analysis focuses on non-college men, but we also present results for non-college women and for college-educated men and women. We use 3-digit industry classifications for persons in the labor force in the Census and ACS data to construct the predicted manufacturing decline measure.

We compute local house prices using data from the Federal Housing Finance Agency (FHFA), which is a repeat-sales housing price index with data for most metropolitan areas. We mapped the FHFA metro areas to the Census/ACS metro areas by hand.[14] To mirror the ACS data, we construct average house price growth between 2000 and the average of house price in the first quarter in 2005, 2006, and 2007. Similarly, when computing house price changes between 2007 and 2011, we use the pooled FHFA data in 2005, 2006, and 2007 and pooled FHFA data from 2009, 2010 and 2011. Estimates of the structural breaks used in the TSLS portion of the paper come from the quarterly data of the FHFA price series.

To compute estimates of elasticity-adjusted price changes ($\widehat{\Delta\omega_k^D}$), which are the measure of local housing demand changes used in the paper, we use information on housing supply and demand elasticities from the literature. The MSA specific housing supply elasticity measures are from Saiz (2010), who constructs them using detailed information on the topography of the MSA. The measure of housing demand elasticity is from the widely-used estimate derived by Polinsky and Ellwood (1979), who calculate an estimate using individual data across 31 urban market, using data on income, housing expenditures and housing prices. In our base specification, we use Polinsky and Ellwood's preferred estimate of -0.7 and assume that elasticity is constant across all MSAs (i.e., $\eta_k^D = 0.7$ for all k). In the Online Appendix, we discuss extensions which confirm that the results are robust to relaxing these assumptions in various ways. In one robustness test, we show that the results are very similar when we assume the housing demand elasticity is as low as -0.3 (among the lowest

[14] See the Online Appendix for details of this matching procedure.

estimates in the literature) and as high as -1.9 (among the highest estimates in the literature).[15] In another robustness test, we show that the results are very similar when we assign to each MSA a demand elasticity drawn at random from a uniform distribution between -0.3 and -1.9. This exercise assumes that the housing demand elasticity is uncorrelated with both the MSA's housing demand change ($\Delta\omega_k^D$) as well as its housing supply elasticity (η_k^S) – both of which we have no *a priori* reason to suppose would not be true.

Table 1 reports summary statistics of the housing market and manufacturing changes among the 235 MSAs with non-missing labor market and housing market data that constitute the main analysis sample. The top row of the table shows that over the boom period of 2000-2007, MSA house prices rose by 47 percent on average. This increase is not driven by a few outlier MSAs. Prices rose sharply throughout the distribution, more than doubling at the 90th percentile MSA and increasing by 5.3 percent even at the 10th percentile. Over the entire 2000s, however, housing prices only increased by an average of 5.8 percent across all MSAs.

The next two entries in the table are summary statistics for the two measures used in the paper to measure sectoral changes in housing and in manufacturing. As discussed earlier, housing price changes alone do not capture changes in local housing demand since there will, in general, be supply responses to these changes in demand. Our estimated housing demand measure, given by the elasticity-adjusted housing price change, is meant to account for both the price and supply effect. The table shows that during the boom the average MSA experienced an 89 percent increase in housing demand, and a decline of 83 percent during the housing bust. The next entry in the table shows summary statistics for the predicted manufacturing change measure. From 2000-2007, the national decline in manufacturing was predicted to lower the share of all men and women employed in manufacturing by 1.6 percentage points. Over all of the 2000s, the average MSA faced a predicted decline in the share of all men and women employed in manufacturing of 3 percentage points. Relative to the housing boom and bust, the manufacturing decline was a sustained phenomenon, with no reversal during the time period studied.

A natural question about the two measures used in the paper is whether they are, in fact, strongly correlated with actual sectoral changes we contend they capture. Figure 2 shows that the predicted manufacturing measure is strongly correlated with actual changes in the share of the prime aged population working in the manufacturing sector, suggesting that the predicted measure does capture local manufacturing demand

[15] See Houthakker and Taylor (2009) for these housing demand elasticity estimates, which span both short-run and long-run demand elasticity estimates.

shocks. Similarly reassuring is the strong positive association in Figure 3 between our estimated housing demand measure and the fraction of the total population in the MSA employed in construction – an activity that would rise with positive local housing demand shocks.

4 OLS Estimates

4.1 Non-Employment Estimates: 2000-2007

Before proceeding to our formal estimates of (5) and (6), we present the raw data used in the analysis. Figures 4a and 4b show simple scatter plots between the 2000-2007 change in the MSA non-employment rate against the 2000-2007 measures of $\widehat{\Delta D_k^M}$ (Figure 4a) or $\widehat{\Delta \omega_k^D}$ (Figure 4b) for the 235 MSAs in our sample.[16] Most of the estimation done in the paper will focus on the 2000-2007 period, since this is a time period unaffected by factors associated with the 2008 recession. As seen from the scatter plots, there is a strong negative relationship between the measures of the sectoral demand changes at the local level and local changes. MSAs that received a larger decline in manufacturing demand or a smaller increase in housing demand had larger increases in non-employment relative to other MSAs.

Panel A of Table 2 presents the OLS estimates of the joint estimation of equations (5) and (6), using the two-step OLS estimator described in Section 2. To interpret the magnitudes, the rows below the estimated coefficients are re-scaled to represent a one standard deviation change.[17] The point estimates in the first column of the top panel of Table 2 imply that a one standard deviation decrease in predicted manufacturing increased non-employment among non-college men by 0.7 percentage points during 2000-2007. Likewise, over the same period, a one standard deviation increase in housing prices decreased the non-employment of non-college men by 1.1 percentage points. Column 2 presents results for college-educated men. The standardized effects are quite small relative to those for non college men – less than half the size in the case of predicted manufacturing decline and about one-fifth the size for estimated changes in housing demand. As columns 3 and 4 show, whereas the effects of manufacturing and housing demand shocks on non-employment for non-college women are comparable to the effects for non-college men, there was little effect on the non-employment of

[16] When graphically illustrating the housing demand change throughout the paper, we first residualize it with respect to the predicted manufacturing decline measure. In our regression framework, we account for changes in manufacturing demand that directly affect housing demand by jointly estimating equations (5) and (6).

[17] The coefficients are always standardized by the cross-city standard deviation in magnitude of the manufacturing shock or the housing shock during the time period analyzed.

college educated women. Non-employment effects for the entire population of men and women aged 21-55 are shown in column 5. These results are closer to the results for persons without a college degree which is not surprising given that those without a college degree constitute roughly two-thirds of the overall population in our sample.

How much of these changes in non-employment from housing demand increases can be attributed to changes in construction employment? Panel B of Table 2 presents results analogous to those in Panel A, but with the change in the share of individuals in the MSA working in construction as the dependent variable. The standardized effect of the housing demand change in Panel B divided by the standardized effect of the housing demand change in Panel A measures how much of the non-employment effect is from construction. For example, a one standard deviation increase in the housing demand for non-college men increased their construction employment by 0.9 percentage points, which accounts for 82 percent (0.9/1.1) of the decline in non-employment of non-college men in response to a housing demand. Notice that for non-college women, only 12 percent of the reduction in non-employment to the housing demand change comes from increased consumption employment, suggesting the overwhelming effect of the housing boom on women operated through increased employment in sectors other than construction.[18]

These results are broadly consistent with the aggregate time series patterns in Figure 1, showing a large increase in construction employment for non-college male but none for non-college women during 2000-2007. The estimates in Table 2 also illustrate the serious limitation of using only construction to measure the effect of housing demand increases on non-employment during the 2000s. While construction employment responded strongly for non-college men, it was not the whole response. Moreover, for non-college women, essentially none of the labor market response to the housing demand increase occurred as a result of increased construction employment. Through a local spillover mechanism, changes in local housing demand affected non-employment through other channels – most likely in local retail and services. Panel B of Table 2 also highlights the local spillover effects of manufacturing decline on employment in the construction sector. Across all individuals, a one standard deviation decline in manufacturing demand reduced construction demand by 0.2 percentage points. As manufacturing declines in a locality, housing demand also falls (Blanchard and Katz 1992). Given

[18]We explored which of a number of obvious candidate sectors responded the most for non-college women but lacked enough statistical power to make definitive statements about relative importance of changes in retail trade, services, or other activity such as real estate agents or mortgage brokers.

our joint estimation of (5) and (6), the effect of a manufacturing decline on non-employment that we report includes both the direct effect as well as the indirect effect through changes in local housing demand.

We also explored whether changes in local housing demand affected local manufacturing employment, perhaps by drawing workers into construction and other local services and away from manufacturing. Consistent with our assumption in Section 2 above, we show in the Online Appendix that a housing boom in a local area has no direct effect on local manufacturing employment changes.

4.2 Effect on Different Sub-Populations: 2000-2007

One interesting question is whether the effects in Table 2 differ by key demographic traits. For example, one might imagine that a sectoral decline affects workers differently based on their age, since industry-specific human capital grows as workers age. Table 3 presents results for non-college men (columns (1) and (3)) and for all workers (columns (2) and (4)) separately by two age-groups: ages 21-35 and ages 36-55.[19] We find that changes in estimated housing demand produced similar non-employment effects for both older and younger workers. By contrast, declines in manufacturing had sharply different effects on workers of different ages. Specifically, negative manufacturing changes increased non-employment among older workers by nearly twice as much as was true for younger workers according to the standardized effects.

We also explored the degree to which the results – particularly for housing – differ across native workers and immigrants. To this end, we have re-estimated the models in Table 2 only on a sample of workers who were born in the U.S. These results are presented in the last two columns of Table 3. Among native workers, the manufacturing results are nearly identical to those reported in Table 2. However, the effect of the housing demand shock on non-employment is roughly 40 to 60 percent smaller in the sample of native workers. For example, for native workers, a one-standard deviation housing demand increase reduced employment of non-college men by 0.4 percentage points (as opposed to 1.1 percentage points in the full sample).

In summary, the effects of the manufacturing and housing demand changes experienced during the 2000s had differential effects across sub-groups based on age or nativity. In particular, the manufacturing decline hit older workers harder than younger workers and housing demand changes affected native workers somewhat less than immigrants. We will return to these heterogeneous results in Section 7 when we discuss the aggregate

[19] To conserve space, many of our future tables only highlight the results for non-college men and for all workers. However, in the Online Appendix we provide analogous tables showing the effects for non-college women, college men, and college women.

effects on these changes on the U.S. economy during the 2000s.

4.3 Non-Employment Effects: 2000-2011

The results in Tables 2 and 3 show the shorter run effect of the sector changes during the 2000-2007 period. How long-lasting were these effects? In Table 4, we examine the effect of manufacturing and housing demand changes over the entire 2000s. Columns 1 and 2 re-display the corresponding results for non-college men and all workers from panel A of Table 2. In columns 3 and 4, we assess whether the 2000-2007 sectoral changes had persistent non-employment effects over the entire 2000-2011 period. The results in columns 3 and 4 show that the effects of predicted manufacturing decline during the 2000-2007 period for both non-college men and for the overall population were in fact quite durable. Indeed, the standardized effects of the manufacturing decline on non-employment growth between 2000 and 2011 were nearly identical to the standardized effects shown in columns 3 and 4. The results for the housing demand change, however, differed sharply with respect to employment changes over the 2000-2007 boom period relative to the broader period from 2000-2011. In particular, we find that changes in estimated housing demand during the housing boom period (2000-2007) had *no* significant long-term effect on non-employment of either non-skilled men or of the entire population during the 2000-2011 period.

In columns 5 and 6, we redefine $\widehat{\Delta D_k^M}$ and $\widehat{\Delta \omega_k^D}$ so that they are computed over the 2000-2011 period. We then assess the effect of these observed 2000-2011 changes on non-employment changes over 2000-2011. The results show that the standardized effect of the 2000-2011 manufacturing change on the long-term change in non-employment was larger than the 2000-2007 manufacturing change. This is not surprising; the standard deviation of manufacturing declines over the longer time period was much higher since manufacturing continued to decline after 2007. It is, however, comforting to note that the estimated coefficients on predicted manufacturing declines are nearly identical across all the time periods.

For the housing demand changes shown in the last two columns, we estimate large and statistically significant negative effects on long-term non-employment changes. The contrast between the shorter-term housing demand results in the first four columns and these long-term results are striking. What accounts for this pattern? We believe that the key explanation, and a reason to interpret the long-term results cautiously, has to do with the nature of transitory housing price variation over the 2000s. Since there was a strong correlation between the magnitude of an MSAs housing price growth during the housing boom and its subsequent price decline during the years of the housing bust, for most MSAs there was little change in estimated housing demand over entire decade.

This point can be seen quite dramatically in Figure 5. This figure plots an MSAs housing price reduction between 2007 and 2011, against its price increase from 2000 t0 2007. The line in the figure is a 45 degree line. The figure shows clearly that for the overwhelming majority of MSA, price increases during the boom were nearly exactly offset by declines during the housing bust. Although not shown in Table 4, we also assessed whether housing demand changes during the 2007-2011 period affected local labor markets during the 2007-2011 period. The answer was that there was very strong relationship between housing demand declines during the housing bust and local labor market outcomes during the bust. The estimated magnitudes were nearly identical the estimates during the boom period.[20]

Since there was little long-term change in estimated housing demand for these MSAs, neither the change during the boom – nor the change during the bust – appreciably affected longer-term changes in non-employment. The figure identifies a small set of large cities appreciably above and below the 45 degree line. In these places, housing prices either grew or declined over the 2000-2011 period. The long-term price variation in these MSAs is almost surely the result of factors not related to something peculiar about the temporary boom and bust in housing, but rather to long-term changes in unobservables in these markets that are likely correlated with changes in labor market outcomes. Over the entire period, places that had persistent housing price declines (like Detroit) or persistent housing price increases (like New York) are most likely the result of factors like changing amenities that also affect local labor market outcomes. As a result, in regressions like those in the last two columns of Table 4, which relate longer-term changes in non-employment to longer-term (2000-2011) changes in estimated housing demand, the coefficient is estimated disproportionately from MSAs with non-zero price changes and will be systematically biased as a result. To ensure that our sub-period results are not being driven by these unobserved factors, we turn to our instrumental variable strategy in section 5.

[20] Our results during the bust period are similar to recent research by Mian and Sufi (2012) and Midrigan and Philippon (2011). Both papers show that during the recession, places with large house price declines had larger increases in non-employment. Our results, however, suggest that in the pre-recessionary period, places that had housing booms also had large declines in non-employment. Over the decade as a whole, the housing boom/bust cycle had very little impact on local labor markets.

4.4 Wage Effects

The empirical model in Section 2 suggests that sectoral declines in manufacturing or increases in housing demand affects labor market outcomes via changes in labor demand. If this reasoning is correct, falling manufacturing demand in an MSA should be accompanied by declining local wages. Likewise, housing demand increases in an MSA should be associated with rising local wages. The wage effects should also be largest for those groups that had the largest employment response to the sectoral shift.

The regressions in Panel A of Table 5 explores these results. These regressions are analogous to the regressions in Tables 2-4, except that the dependent variable is now mean wage growth in the MSA for a given group during a given time period.[21] As seen from Table 5, a one standard deviation manufacturing decline reduces wage growth for non-college men between 2000 and 2007 by 1.8 percentage point. For all workers, the wage response between 2000 and 2007 to the manufacturing decline was smaller at 1.1 percentage point. With respect to a one-standard deviation housing demand increase, the wage response between 2000 and 2007 was 2.3 percentage points and 1.8 percentage points for non-college men and all individuals, respectively. These results are consistent with our interpretation that these sector shifts affect local labor markets through their effect on labor demand.

4.5 Migration Effects

In Panel B of Table 5, we estimate the extent to which local changes in manufacturing and housing result in migration across MSAs. As one location receives a negative shock to labor demand, individuals in part respond to that shock by migrating elsewhere (Blanchard and Katz 1992; Notowidigdo 2012). We find that in response to a one standard deviation manufacturing decline (housing demand increase) change during the 2000-2007 period, the MSA population of prime age non-college men fell by 2.3 percentage points (increased by 2.4 percentage points) during that same period. The results are nearly identical for all prime age men and women. The migration response to the manufacturing decline was actually larger over the longer 2000-2011 period while the response to housing demand increases was smaller. This is not surprising given that

[21] When computing mean wages within an MSA during a given time period, we start with the same samples described in Section 3. However, we also impose the following restrictions to the individual data: (1) the individual must be currently working at least 30 hours during a typical week at the time of the survey, (2) the individual's income in the year prior to the survey must exceed $5,000, and (3) the individual must have worked at least 48 weeks during the prior year. With these restrictions, we then complete mean wages at the MSA level in each of the time periods. Given these restrictions, our wage data should be considered for full-time workers with relatively few non-employment spells.

the 2000-2011 period witnessed the continuing decline in manufacturing, and the growth and reversal of the housing boom. When we conduct aggregate counterfactuals of what would have happened had there been no housing demand change or had there been no manufacturing decline, we explicitly account for these migration responses in robustness tests.

5 TSLS Estimates

As we noted above, one concern with the OLS estimates of the effect of changes in housing demand is that, as expression (6) shows, this measure may be endogenous in non-employment regressions. Additionally, given that our housing demand change measure is constructed with the assumption that there are no housing supply shocks, it is likely an error-ridden version of true housing demand changes. We will address both of these potential concerns using Two Stage Least Squares (TSLS) analysis.

The instrumental variable we use for predicted housing demand change (i.e., elasticity-adjusted housing price change) is motivated by comparisons of house price trends across MSAs, such as those illustrated in Figure 6. This figure shows four pairs of cities, with each pair experiencing similar overall changes in house prices between 2000 and 2006. However, within each pair, housing prices evolved smoothly over time for one city, but changed discontinuously, or "sharply", at some point in the mid 2000s for the other. For example, both Monmouth-Ocean, NJ and Phoenix, AZ experienced increases in house prices of roughly 50 percent over this time period. Whereas the vast majority of this increase in Phoenix happened following a sharp break in housing prices in the middle of 2004, house prices in Monmouth-Ocean increased steadily over the entire time period. Using these figures as motivation, we construct MSA-specific estimates of the magnitude of the structural break in housing prices, where we search for a single structural break during 2003 and 2005.[22] Specifically, we use quarterly real house prices and run MSA-specific OLS regressions with a single structural break and search for the location of the break which maximizes the R^2 of the regression. The magnitude of the structural break coefficient is then used as our instrument for the change in estimated housing demand.

How well does this variable predict variation in housing demand changes across MSAs? Table 6 relates the 2000-2007 change in housing demand to the estimated structural break from the procedure above. Columns 1 and 2 of the table shows that the size of a structural break in a city's quarterly price series strongly predicts

[22] See Ferreira and Gyourko (2011) for a detailed discussion of how many MSAs had a discrete jump in house prices during the mid-2000s relative to their historical trends.

the size of the city's 2000-2007 change in housing prices. The large and strongly statistically significant point estimates are robust to the inclusion of the set of controls used previously and to controlling for the predicted manufacturing decline measure. The final column in the table examines how employment in manufacturing among non-college men is affected by the structural break variable. We find no relationship between these measures suggesting that the instrument is orthogonal to changes in manufacturing demand. The results in the first three columns of Table 6 are the first-stage estimates for a TSLS analysis that uses the estimated structural break as instrument variables for housing demand changes. Importantly, the F-statistic on the structural break measure is always above 30, which suggests that there is no "weak instrument" concern.

The identifying assumption when using the structural break variable as an instrument for estimated housing demand changes is that unobserved labor demand and labor supply shocks are incorporated into housing prices gradually, while exogenous shocks to housing demand (such as sub-prime mortgage expansions, low interest rates, or local bubbles) may be incorporated either smoothly or sharply. As Figure 6 shows, this means that, in practice, our instrument identifies the effect of local housing demand changes primarily from cities with sharp price changes, such as Portland and Phoenix, rather than cities such as New York and Providence – since these cities experienced large increases in house prices, but experienced these changes relatively gradually. Consistent with the idea that the instrumental variable isolates housing demand variation, we show in the Online Appendix that the structural break measure is strongly correlated with an increase in construction employment around the same time period.

Table 7 reports TSLS results analogous to the main results in Table 2. Across all five columns, we consistently find that the estimated effects of house price booms during the 2000-2007 period are very similar to our OLS results. The point estimates are generally slightly larger than the corresponding OLS results, which is consistent with the idea that either some of the variation in house price changes was actually the result of changes in unobserved labor demand or labor supply or that there is some measurement error in our housing demand estimates. However, the broad similarity between the OLS and TSLS results suggests that most of the variation in housing prices at the MSA level between 2000 and 2007 was not significantly confounded by omitted variables or by housing supply shocks.[23]

Lastly, we estimate a large number of additional OLS and TSLS models, and we show that our results

[23] In the Online Appendix, we present TSLS for all of the key Tables 2-5. Across all of these specifications, we consistently find broad similarities between the OLS and TSLS results.

are robust to a wide variety of alternative specifications which vary the sample, the instrumental variable, and the controls used. We discuss these results in detail in the Online Appendix; in general, these alternative specifications produce results that are very similar to our preferred OLS and TSLS specifications. We therefore conclude that we find robust evidence that housing demand shocks significantly reduce non-employment for non-college men and women, and that the magnitude of this effect is large enough to offset the adverse effects of declining manufacturing during the 2000-2007 time period.

6 Conceptual Framework

What theoretical framework reconciles our various results? We develop a stylized model of occupational choice and non-employment, in the spirit of Roy's (1951) classic framework, which provides some insights about non-employment in the presence of shocks to different sectors. We suppose that there are two sectors in which workers can be employed: manufacturing, M, and housing-related sectors, H. Extending the standard Roy framework, we suppose workers have some reservation utility associated with allocating their time to the non-employment sector, N. Assume a mass of workers with heterogeneous skill endowments and reservation wages, which are jointly distributed according to the PDF $f(s, r)$. To highlight the role of self-selection, we let both skill endowment and the reservation wage be exogenous characteristics of the individual. Workers with skill endowment s can either supply s efficiency units of labor in sector M, $(1 - s)$ efficiency units of labor in sector H, or be non-employed in sector N.[24] A worker will choose non-employment if his reservation wage if larger than his highest wage across to two sectors, or $r > \max\{sw_M, (1-s)w_H\}$, and will be employed otherwise.

We assume that aggregate market output is given by the following production function:

$$Y = \alpha L'_M + \beta L'_H$$

where α and β are sector-specific demand shifters in M and H, and L'_M and L'_H are total labor supplies in the two sectors denominated in efficiency units. Cost minimization implies that wages per efficiency unit are

[24] Given this, s represents the productivity of the worker in sector M *relative* to the worker's productivity in sector H. In this sense, s indexes a workers comparative advantage between the two sectors. The main implications of the model carry through if we also allow workers to have an absolute advantage in any of the sectors.

pinned down by the demand shifters, so that $w_M = \alpha$ and $w_H = \beta$. Total labor supply across sectors is determined by the endogenous self-selection of workers given the prevailing wages. A worker with (s, r) works in sector M if $sw_M > (1-s)w_H$ and $sw_M > r$. For the marginal worker, who is indifferent between working in M and working in H, $s^* w_M = (1-s^*)w_H$. Total labor supplies in A and B are therefore given by the following:

$$L'_A = \int_{s^*}^{1} \int_{0}^{s\alpha} s f(s,r) dr ds$$
$$L'_B = \int_{0}^{s^*} \int_{0}^{(1-s)\beta} (1-s) f(s,r) dr ds$$

Since population shares are much easier to measure empirically than total labor supplies in efficiency units, we solve for the population shares in each sector by noting that individuals must choose to be in one of the three sectors. Thus, $L_M + L_H + L_H = 1$ and

$$L_M = \int_{s^*}^{1} \int_{0}^{s\alpha} f(s,r) dr ds \tag{7}$$
$$L_H = \int_{0}^{s^*} \int_{0}^{(1-s)\beta} f(s,r) dr ds \tag{8}$$
$$L_N = 1 - L_M - L_H \tag{9}$$

Both the equilibrium of this simple model and comparative statics results for shocks to industry productivity parameters can be illustrated graphically.[25] Figure 7 illustrates how workers, in equilibrium, self-select into sectors at all possible combinations of skill endowment and reservation wages, for different values of the productivity shocks. The y-axis in the figure is the reservation wage (r) and the x-axis is the relative skill endowment (s), with the entire plane representing all possible (s, r) combinations. The density $(f(s, r))$ would be represented as contour lines on the plane.

Figure 7a depicts an initial equilibrium, with workers for whom $s > s^*$ choosing to work in the manufacturing sector, M, as long as $s\alpha > r$. Workers with $s < s^*$ and $s\beta > r$ will work in housing-related sectors, H. Workers with a high reservation wage or who have no relative skill advantage in either sector are more likely to be non-employed at any point in time. Figure 7b illustrates the effect of a negative productivity shock to

[25] With a specific functional form assumption for $f(r, s)$ and values for α and β, one can solve for equilibrium values of s^*, L_M, L_H, L_N. If s and r are jointly uniformly distributed, then the stylized model admits a simple, closed-form solution.

manufacturing such as that studied throughout the paper. A negative manufacturing shock, represented by a fall in α, is predicted to lower the share of persons employed in manufacturing because of two margins of adjustment. As the figure illustrates, some workers switch from the manufacturing sector, M, to housing-related sectors, H, and other workers are predicted to leave manufacturing to enter non-employment, N (represented by the area $M \rightarrow N$). Theory offers little guidance about the relative magnitude of these two effects, as they depend on the distribution of reservation wages and skill among workers. For example, if most workers have very low reservation wages, then a negative shock to one sector will mostly generate switching into the other sector, with little change in non-employment. This corresponds to a situation of inelastic labor supply, as in occupational choice models such as that by Autor, Levy, and Murnane (2003), where sector-specific shocks reallocate workers across sectors but do not change aggregate non-employment. Our various empirical results above suggest, by contrast, that many workers (especially the less-skilled) have reservation wages close to their market wages, since negative manufacturing shocks lead to substantial changes in non-employment in the short-to-medium run. This is also the mechanism at play in Bound and Holzer (1993).

Figures 7c and 7d illustrate the situation, such as what occurred in the early 2000s, where a negative manufacturing shock occurs simultaneously with a positive shock in the housing-related sector. In Figure 7c, we highlight only the adjustments along the non-employment margin. Figure 7d highlights the margin of substitution resulting from the movement of workers across sectors without the potential for a non-employment spell. The key result from Figure 7c is that the overall non-employment effect from a decline in manufacturing is attenuated, or "masked", for two reasons.[26] First, there may be *within-person* masking. This is what occurs when individuals who would have otherwise entered non-employment because of decline in manufacturing are instead employed because of the temporary boom in housing. This area is represented by the diamond area $M \rightarrow N \rightarrow H$. Figure 7c also highlights masking that operates across *different* people, even perhaps across different spatial areas. With this type of masking persons drawn out of non-employment because of growth in housing ($N \rightarrow H$) are not the same as the persons who enter non-employment from manufacturing. The final panel shows how the changes in the two sectors will lead to a reallocation of some workers from manufacturing to housing, with no change in non-employment.

Below, we use individual-level data from the Displaced Worked Survey to show that within-person masking

[26] Notice that one can say, equivalently, that the manufacturing decline is predicted to mask the degree to which a positive change in housing-related sectors *lowers* non-employment.

was prominent during the 2000-2007 period in the U.S. Some workers displaced by the sectoral decline in manufacturing were, all else equal, more likely to be re-employed if their local area also experienced a positive housing demand change. We then do counterfactual analysis to show the overall effect of both types of masking. We show that that the aggregate labor market in the U.S. did not show the effects of the sectoral decline in manufacturing because the temporary housing boom masked the more structural effects on non-employment because of substantial masking both *within* individuals, *across* individuals, and *across* MSAs.

7 Empirical Evidence on Masking

In this section, we study how the housing boom and bust and manufacturing decline interacted to affect observed changes in non-employment during the 2000s. We first present some graphical evidence. We distinguish MSAs that received large housing demand increases during the 2000-2007 period from those MSAs that did not receive large housing demand increases during the 2000-2007 period. We define a large housing demand increase by taking the MSAs in the top tercile based on the estimated housing demand measure, $\widehat{\Delta\omega_k^D}$ (residualized for the MSA decline in predicted manufacturing). We refer to these MSAs as housing boom MSAs. We then plot the relationship between predicted decline manufacturing between 2000 and 2007 ($\widehat{\Delta D_k^M}$) in an MSA and the change in the share of non-college men in non-employment during the same time period, separately by "housing boom MSAs" and all other MSAs.

Figure 8a presents the 2000-2007 plots. In the figure, "housing boom MSAs" are represented with triangles, and the remaining two thirds of MSAs with circles. The gray line is the bivariate regression line for MSAs with housing price changes in the bottom 2/3 of sample. The large and precisely estimated negative slope coefficient (-1.24, s.e. 0.132) implies that predicted manufacturing declines sharply increase non-employment among non-college men. Most of the triangles in the figure lie below the regression line, implying that MSAs with especially large housing demand changes experienced smaller increases in non-employment rate among non-college men than did other types of MSAs with similar predicted changes in manufacturing. Formally, housing boom MSAs systematically had 1.7 percentage point lower non-employment growth for any given manufacturing decline than non-housing boom MSAs (standard error of the difference = 0.004).

Figure 8b is analogous to Figure 8a except that both the predicted manufacturing decline and the change in non-employment for non-college men are defined over the 2000-2011 period. Consistent with the results in

Table 4, the results show that the temporary housing demand shock during 2000-2007 had no lasting effects on non-employment over the entire 2000-2011 period. This can be seen from the fact that "housing boom" MSAs are distributed even around the regression line for the other MSAs. Formally, there is no difference in the intercept of the regression line based on the MSAs that did and did not experience a housing boom between 2000 and 2007 (intercept difference = 0.001 with a standard error of 0.006).

These results suggest that some of the masking occurred *within* MSAs during the 2000-2007 period. Among MSAs that experienced a large decline to manufacturing demand, the ones that also experienced a housing boom had lower increases in non-employment during the 2000-2007 period. The masking results were undone as the housing bust occurred. Over the entire 2000-2011 period, MSAs that experienced a large decline in manufacturing had similar levels of non-employment regardless of what happened to housing prices in that MSA during the 2000-2007 period.

7.1 Estimating "Within-Individual Masking" using Displaced Workers

The aggregate patterns in Figure 9 suggest that the there was likely substantial masking during the 2000-2007 period and that within-person masking was an important aspect of this. How important was within-individual masking during the housing boom? For a precise quantitative estimate of within-person masking, we use individual-level data from several years of the CPS Displaced Worker Survey. The DWS is conducted every two years. Besides the standard battery of CPS questions about current employment and demographics, respondents are asked in each wave whether they were displaced from their job at any point in the preceding three years, along with information about some features of the previous job. We construct a sample consisting of all non-college men aged 18-64 in the 1994-2006 waves of the survey who were displaced from the manufacturing sector. Displacements in this sample occurred between 1992 and 2004. At 3051 persons, this sample is relatively small but this is the only micro-data with which to study outcomes for manufacturing displaced workers during the years under study.

We create an indicator variable to denote displacement between 1996 and 2005 - an interval during the national housing boom.[27] Persons for whom this indicator was zero were either displaced between 1991 and 1995 (before the housing boom), or do not live in a metropolitan area. Our second indicator variable is whether

[27] Note that workers are identified by the year of their displacement not the year in which the survey contacts them about their follow-up employment status. For example, if a worker is displaced in 1996, the survey will measure the labor market status in some later year.

the individual lived in a "housing boom MSA" – as defined above. We conduct a difference-in-difference analysis to determine how being displaced within a housing boom MSA affected subsequent employment outcomes for these displaced manufacturing workers. We study two outcomes: whether the person reported non-employment as of the survey year, and whether the person was employed in construction as of the survey year.

Figures 9a and 9b illustrate our difference-in-difference approach graphically. Figure 9a plots the likelihood of non-employment for displaced manufacturing workers, separately by whether the worker lived in a "housing boom" MSA. The figure shows that for persons displaced prior to the start of the national housing boom the two series tracked each other quite closely.[28] Displaced manufacturing workers, irrespective of their MSA, ended up in non-employment roughly 35 percent of the time. During the period of the national housing boom, the two series diverged, with displaced manufacturing workers in "housing boom" MSAs ending up in non-employment at a rate roughly 10 percentage points lower than their counterparts in MSAs without large housing price increases. Given the base non-employment rate of 35 percentage points, the estimated difference between housing boom and non-housing boom MSAs is quite large. Figure 9b depicts similar patterns for whether displaced manufacturing workers get re-employed in construction. Again, we see no difference across the two series prior to the start of the national housing boom. When the national housing boom begins, the series diverge, with the likelihood of re-employment in construction for displaced manufacturing workers in "housing boom" markets surging by more than 10 percentage points particularly during the 1999 through 2003 periods. This increase was massive relative to a base rate of around 2 percent.

The regression model we estimate is given by:

$$\begin{aligned} y_{i,m,t} = {} & \alpha_1 \; I(\text{Housing Boom MSA}_m) + \alpha_2 \; I(\text{Boom Period}_t) + \\ & \alpha_3 \; I(\text{Housing Boom MSA}_m \times \text{Boom Period}_t) + X_{i,m,t} + e_{i,m,t} \end{aligned} \tag{10}$$

where y is either non-employment or re-employment into construction, the indicator variable are as defined above, and vector X contains individual-level controls. The individual controls include education, union status in last job, and a 5th order polynomial in age. Table 8 presents the results, which report standard

[28] To reiterate, in Figure 9 the x-axis marks the year of displacement. The 1996 displaced workers are being measured – on average – in the 1998 labor market. Likewise, the 2004 displaced workers are being measured – on average – in the 2006 labor market. With that in mind, Figure 9a suggests that between the 1998 labor market and the 2006 labor market, the labor market outcomes of displaced manufacturing workers differed between housing boom MSAs and other MSAs (and non-metro areas).

errors clustered by state (as above).

The coefficient α_3 on the interaction term is the difference-in-differences estimate, but the coefficients on the non-interaction terms are also of interest. The housing boom indicator tells us whether non-employment rates (in column 1) or construction re-employment (column 4) are different, on average, in housing boom MSAs versus other areas. As shown in figures 8a and 8b, there are no visible difference in labor market outcomes between housing boom and other MSAs in the early-to-mid-1990s. This is consistent with the regression results in Table 8. More interesting is the level coefficient on displacement during the years of the housing boom. Here, the positive and significant effect of the coefficient in the construction employment equation in column 4 implies that displaced manufacturing workers are more likely to go into construction in *all* MSAs during boom period, regardless of whether or not the MSAs housing price growth was in the top third of all markets. This is not surprising given the results in Figure 1a showing that manufacturing and construction are two important sectors for non-college men.

For each outcome in Table 8 we present three sets of difference-in-difference results. The first specification (in columns 1 and 4) pool all "housing boom MSAs" together. The second regression (columns 2 and 5) uses MSA fixed effects and adds fixed effects for each year of displacement. The third regression (columns 3 and 6) adds the individual-level controls to the second set of regressions. The difference-in-difference results for non-employment, presented in the first row of the table, suggest a substantial amount of what we term "individual-level masking". We find that manufacturing workers displaced in markets with especially large housing demand increases during the 2000-2007 period were around 11 percentage points less likely to enter non-employment. This result holds across various specifications, and is very large relative to the mean of the outcome variable of 33 percent. Given these estimates, individuals displaced from manufacturing in a housing boom MSA were roughly 33 percent more likely to be re-employed in the near term after their displacement spell (0.11/0.33).

The results for construction are equally striking. In the results in column 4, in which we pool all "housing boom" MSA together, the point estimates suggest that displaced manufacturing workers were more likely to be employed in construction if they became displaced in markets with big housing demand increases. This effect is very imprecisely estimated, however. In the alternative specifications, in which we use MSA fixed effects and year of displacements effects, we find larger and strongly significant effects. The point estimate of

0.038 suggests displaced manufacturing workers in markets during the years of the housing boom in markets with substantial appreciation were likely to find re-employment in construction at a rate that was more than 50 percent of the mean. These results suggest that as much as one-third of the non-employment "masking" came through construction employment.

Collectively, these results provide powerful evidence of individual-level masking. Had there been no temporary housing boom from the late 1990s through the mid 2000s, workers displaced from manufacturing because of the ongoing decline in that sector would have been significantly more likely to end up in non-employment.

7.2 Aggregate Masking and Counterfactuals

In this section, we use estimated effects of manufacturing decline and housing booms to provide counterfactual estimates of aggregate non-employment nationally during the 2000-2011 period. This analysis also summarizes the degree to which the temporary housing boom during the early 2000s masked the labor market deterioration at the national level resulting from manufacturing decline. Masking at the national level is a combination of cross-individual masking and the within-individual masking documented in the previous section.

To perform the counterfactual exercise, we use national time series changes in the non-employment rate, housing demand changes, and manufacturing employment shares, and combine these with the main estimates from Table 2 to compute the separate contribution of both declining manufacturing and housing demand changes on aggregate non-employment. Panel A of Table 9 reports the exercise for all prime age men and women. The share of prime age men and women employed in manufacturing (out of all prime age men and women) declined by 3.2 percentage points between 2000 and 2007, which according to the estimates in column 5 of Table 2 would correspond to a predicted increase in non-employment of 2.1 percentage points.[29] Similarly, given the mean change in estimated housing demand over the 2000-2007 period of 0.88 (see Table 1), our empirical estimates imply a decline in non-employment of -0.9 percentage points. The combined predicted effect of the two shocks is that they increased non-employment for non-college men by 1.2 percentage points between 2000-2007. The actual increase in non-employment for all prime age men and women was 1.9

[29] For the national trends in non-employment and manufacturing over the 2000-2007 period and the 2000-2011 period, we use data from the CPS. The sample for this data is the same as the ones used in Figure 1. We use the CPS data instead of the Census/ACS data because the non-employment rate levels seem systematically too high in the 2000 Census (relative to the 2000 CPS and relative to the 2001 ACS). This fact has been carefully documented Clark et al. (2003). The CPS, therefore, allows us to get a more consistent time series trend. As long as this mismeasurement affects the local labor markets in our sample similarly, then this will not significantly bias our local labor market estimates.

percentage points. Therefore, these two forces can account for nearly two-thirds of the observed changes in non-employment during the early-to-mid 2000s.

In the absence of any change in housing demand during this time period, non-employment rate growth would have been 30% larger. The next row of Panel A explores the entire 2000-2011 period. We find that the predicted change in non-employment due to manufacturing decline and housing demand changes is 3.2 percentage points, which is 44% of the actual increase in non-employment during the longer time period. Panel B shows broadly similar results for non-college men (as compared to all men and women). While the estimated effects imply greater absolute increases in non-employment for non-college men, the percentage of overall non-employment growth accounted for by manufacturing decline and housing demand changes is very similar.

These predicted values reveal three lessons regarding the effect of manufacturing on non-employment rates during the 2000s. First, if it was not for the temporary masking from the housing boom during the 2000-2007 period, non-employment rates for non-college men (all men and women) would have been 1.2 (0.9) percentage points higher in 2007. In terms of the number of workers, this means that 1.3 million prime age workers would have been non-employed in 2007 had it not been for the temporary housing boom masking the structural decline in manufacturing. Second, most of the effect of manufacturing on U.S. labor markets occurred prior the 2008 recession. For both non-college men and all workers, roughly two-thirds to three-quarters of the manufacturing decline pre-dated the recession. This can be seen by comparing the different rows of column 3 of Table 9 in each panel. Third, we analyzed the extent to which the decline in employment showed up as increased non-employment or as increases in individuals being out of the labor force. These results are shown for non-college men in Panels C and D of Table 9. The empirical model predicts that the decline in manufacturing over the entire decade resulted in a 2.1 percentage point increase in non-participation and a 2.5 percentage point increase in unemployment. Given the observed changes in non-participation and unemployment over the decade, this implies that declining manufacturing demand can explain roughly 50 percent of the increase in non-employment we have observed for non-college men over the decade and roughly one-third of the observed increase in unemployment.

Collectively, the results suggest that a non-trivial portion of the increase in non-employment, non-participation, and unemployment of both non-college men and all workers can be attributed to the decline in the manufacturing sector. We emphasize that this does not rule out an important role for other cyclical forces. What it does imply, however, is that at least part of the reason that the U.S. labor market has been so weak has to do with structural forces associated with the ongoing decline in the manufacturing sector. The reason that part of the effects of these structural forces did not show up earlier is because the temporary housing boom masked some of these effects in aggregate statistics during the early-to-mid 2000s.

Although we believe these counterfactual results are reliable, there are several reasons to exercise considerable caution in interpreting these results. First, one should always be careful in applying "local" estimates to a national context, and so we discuss various concerns about such an extrapolation. Our local estimates allow for migration as an endogenous outcome to manufacturing and housing shocks (Table 5). We find that a one standard deviation manufacturing and housing shock both affect non-employment by roughly 1 percentage point. However, the same manufacturing and housing shocks also affect population growth by roughly 2 percentage points. Using these estimates, we can bound how much migration will affect our counterfactual predictions. To get one bound, we assume that all of the migrants would have been non-employed had they been forced to stay. In this case, the aggregate non-employment rate in response to a one standard deviation manufacturing shock would have increased by an additional 2 percentage points (from 1 to 3). The counterfactual estimates above would thus be severely *underestimated*. By contrast, if we assume that all of the migrants would have been employed had they been forced to stay, then the estimated response to a one-standard deviation manufacturing shock would fall by roughly 0.02 percentage points (from 1 to about 0.98). This effect is so small because the number of people migrating out of the MSA in response to manufacturing shock is very small relative to the number of people who are employed in the MSA. Therefore, assuming that migrants are either more employable than the average non-migrant or roughly similar to average non-migrant has a negligible effect on our results. If, however, the marginal migrant is much less employable, then the counterfactual estimates we present are substantially conservative.

A second important limitation of our results is that we are only isolating local labor market responses and ignoring any potential general equilibrium responses to the manufacturing and housing shocks. In particular, changes in house prices may have a direct effect on U.S. manufacturing demand. For example, Mian and Sufi (2011) show that households that experienced large increases in housing prices not only increased their purchase of local services, they also increased their nondurable expenditures through a housing wealth and/or liquidity effect. In this case, local housing booms can affect the national demand for manufacturing goods. This type of feedback will again cause us to underestimate the extent of masking that occurred during the 2000-2007 period, since the decline in manufacturing between 2000 and 2007 would have been even greater had it not been for the housing boom within the U.S. that effectively "propped up" manufacturing demand. As with the migration results, ignoring this general equilibrium channel appears to make our counterfactual estimates from the 2000-2007 period conservative.

Another potential concern with our results is that the decline in manufacturing during the 2000-2007 period could have been one of the proximate causes of the housing boom. However, our results suggest that channel is highly implausible. We find across local labor markets that declines in manufacturing put downward pressure on house prices, so any nationwide effect linking manufacturing busts to housing booms would have to overwhelm these local effects.

Finally, for reasons similar to the general equilibrium effects during the boom years discussed above, we may be overstating the effect of manufacturing decline during the housing bust period. If declines in housing prices dampened the demand for manufactured goods during the 2007-2011 period, the change in manufacturing between 2007 and 2011 for our counterfactuals may be too large. We do two additional things to account for this possibility. First, we redo our counterfactuals assuming that the trend in manufacturing between 2000 and 2007 continued through 2011. This assumption strikes us as reasonable, given that there has been a relatively steady decline in manufacturing within the U.S. for 40 years (see Figure 1). Linearly extrapolating the trend in manufacturing through 2011, we find nearly identical results to what was reported in Table 9, since the actual decline in manufacturing employment between 2007 and 2011 is very close to what one would extrapolate based on the 2000-2007 trend. Second, as discussed above, we can ignore the decline in manufacturing during the recession and only focus on the decline in manufacturing that occurred prior to the recession. Even in this instance, we still get sizeable effects of the manufacturing decline during 2000-2007 on current employment prospects within the U.S.

8 Conclusion

This paper studies how manufacturing decline and housing booms affect labor market outcomes, with a particular emphasis on non-employment among the two-thirds of workers without a college degree. We estimate a variety of cross-MSA models which exploit the variation in both the magnitude of the negative shock to manufacturing as well as the sudden and dramatic increases in housing demand.

We find that roughly 40 percent of the increase in non-employment during the 2000-2011 period can be attributed to the decline in manufacturing. These non-employment effects were very large for non-college men, but we find that local manufacturing shocks significantly raised non-employment for other groups, as well, such as non-college women. The large adverse labor market effects of manufacturing decline are present during the years of the housing boom (2000-2007), during the collapse in the housing market (2007-2011) and over the entirety of the 2000s, over 2000-2011. We also find that increases in housing demand during this period sharply lowered non-employment during 2000-2007, especially among non-college men and women. The reversal of housing market during 2007-2011 among cities experiencing unusually large increases in housing demand during 2000-2007 implies that – over the entire 2000-2011 period – local housing booms do not significantly contribute to longer run changes in labor market outcomes.

The results imply that the positive labor market effects of the temporary housing boom "masked" the negative effect of sectoral decline in manufacturing that would have otherwise been more evident in the mid-2000s. The collapsing of the housing market during 2007-2011 not only had an independent adverse effect on labor market outcomes for some sub-groups but also "unmasked" the negative manufacturing effect that would have been seen earlier. Using individual-level data from surveys of displaced workers, we present some suggestive evidence that part of this masking occurred at the level of individual workers, as well as across workers from different sub-groups and in different locations.

Our results may speak to the literature studying aggregate business cycle dynamics. Often, sectoral booms and busts are linked to aggregate business cycle dynamics. All else equal, a sectoral boom will increase wages and employment during the expansion and result in wages and employment falling during the contraction. Our results, however, highlight that sectoral booms and busts have very different aggregate employment dynamics when another sector in the economy is experiencing consistent, ongoing decline. In this case, a boom and bust in the first sector results in muted labor market effects during the boom period and large labor market effects during the bust. The behavior of labor force participation since the early 1980s suggests the potential importance of a mechanism like this in the U.S. labor market. Since 1980 the labor force participation rate of men in the U.S. has been relatively stable during expansions and has adjusted sharply around contractions.

This point has been emphasized recently by Jaimovich and Sui (2012), and our results suggest that booms and busts in other sectors combined with a sectoral decline in manufacturing will generate these patterns.

Finally, we think that our results may inform the current policy debate about how best to stimulate employment. The type of non-employment we have identified is the result of the longer run sectoral decline in manufacturing. Temporary boosts in labor demand due to hiring subsidies or infrastructure investments are not likely to have permanent effects on the labor demand of non-college individuals. As those hiring subsidies and infrastructure investments expire, the labor demand for non-college labor will still be depressed because of the decline in manufacturing sector. In this sense, our paper is among the first to document a significant role for structural forces in explaining the current high level of non-employment in the U.S. As noted above, over longer periods of time, non-employed workers (as well as subsequent generations of workers) may find it beneficial to invest in human capital accumulation. Therefore, addressing barriers to skill acquisition may have the most lasting effect on increasing the employment prospects of those workers who leave the labor force as a result of the ongoing decline in the manufacturing sector.

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Table 1
Descriptive Statistics for Predicted Changes in Housing Demand and Manufacturing

Change defined across following years:	2000-2007						2000-2011					
			Std.	Percentiles					Std.	Percentiles		
	N	Mean	Dev.	10th	50th	90th	N	Mean	Dev.	10th	50th	90th
Observed Change in Housing Prices	235	0.472	0.393	0.053	0.361	1.207	235	0.058	0.183	-0.176	0.047	0.329
Shock Measures:												
Predicted Housing Demand Change	235	0.884	0.668	0.160	0.707	1.777	235	0.070	0.402	-0.523	0.079	0.482
Predicted Manufacturing Decline	235	-0.016	0.009	-0.027	-0.015	-0.008	235	-0.030	0.016	-0.052	-0.027	-0.014

Notes: This table reports the summary statistics for the baseline sample of 235 metropolitan areas (MSAs) across the two time periods studied in the regressions that follow. The Predicted Housing Demand Change is constructed by multiplying the change in housing prices (from FHFA house price index) by the sum of the price elasticity of housing demand (assumed to be 0.7 based on Polinsky and Ellwood 1976) and a MSA-specific housing supply elasticity estimate (from Saiz 2010). This procedure creates a proxy for the change in housing demand in an MSA. The Predicted Manufacturing Decline variable is constructed using the 2000 Census, the 2005-2007 American Community Survey, and the 2009-2011 American Community Survey following the procedure in Bartik (1991) and defined in more detail in the main text. All of the reported sample statistics are computed using the 2000 population of prime-aged men and women in the MSA (from Census) as weights, since these weights are used in the regressions that follow.

Table 2
Non-Employment and Construction Employment Response to
Housing Demand Change and Manufacturing Decline

Sample:	Non-College Men	College Men	Non-College Women	College Women	All Men and Women
	(1)	(2)	(3)	(4)	(5)
Panel A: Dependent Variable is Change in Nonemployment Rate, 2000-2007					
Predicted Housing Demand Change	-0.014	-0.003	-0.010	-0.003	-0.010
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
	[0.003]	[0.266]	[0.001]	[0.142]	[0.000]
Predicted Manufacturing Decline	-0.641	-0.356	-0.833	-0.288	-0.665
	(0.246)	(0.149)	(0.171)	(0.162)	(0.148)
	[0.013]	[0.021]	[0.000]	[0.082]	[0.000]
Standardized (1σ *) effects:*					
Housing demand change	-0.011	-0.002	-0.008	-0.003	-0.008
Manufacturing decline	-0.007	-0.004	-0.009	-0.003	-0.007
R^2	0.71	0.17	0.69	0.12	0.77
Panel A: Dependent Variable is Change in Share Employed in Construction, 2000-2007					
Predicted Housing Demand Change	0.012	0.002	0.002	0.001	0.006
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
	[0.000]	[0.158]	[0.002]	[0.111]	[0.002]
Predicted Manufacturing Decline	0.333	0.075	0.110	0.008	0.184
	(0.219)	(0.096)	(0.036)	(0.035)	(0.107)
	[0.136]	[0.443]	[0.004]	[0.808]	[0.094]
Standardized (1σ *) effects:*					
Housing demand change	0.009	0.002	0.001	0.001	0.004
Manufacturing decline	0.003	0.001	0.001	0.000	0.002
R^2	0.46	0.08	0.21	0.05	0.43
N	235	235	235	235	235
Include baseline controls	y	y	y	y	y

Notes: This table reports results of estimating equations (5) and (6) by OLS for various demographic groups. A 0.1 unit increase in the Predicted Housing Demand Change represents a 10 percent increase in housing demand, while a 0.1 unit change in Predicted Manufacturing Decline variable corresponds to a 10 percentage point change in predicted share of population employed in manufacturing. The baseline controls include the initial (year 2000) values of the share of employed workers with a college degree, the share of women in the labor force, and the log population in the MSA. The standardized effects rescale the coefficient by a one standard deviation change using the cross-MSA standard deviation. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 3

Non-Employment Response to Housing Demand Change and Manufacturing Decline, By Age Group and Immigration Status

Dependent Variable is Change in Non-Employment Rate, 2000-2007						
Restriction:	Age 21-35		Age 36-55		Drop Immigrants	
Sample:	Non-College Men	All Men and Women	Non-College Men	All Men and Women	Non-College Men	All Men and Women
	(1)	(2)	(3)	(4)	(3)	(4)
Predicted Housing Demand Change	-0.015	-0.014	-0.013	-0.009	-0.008	-0.007
	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)
	[0.011]	[0.000]	[0.002]	[0.005]	[0.028]	[0.007]
Predicted Manufacturing Decline	-0.400	-0.450	-0.831	-0.824	-0.872	-0.789
	(0.203)	(0.130)	(0.247)	(0.191)	(0.173)	(0.113)
	[0.056]	[0.001]	[0.002]	[0.000]	[0.000]	[0.000]
Standardized (1σ) effects:						
Housing demand change	-0.011	-0.010	-0.010	-0.007	-0.006	-0.005
Manufacturing decline	-0.004	-0.005	-0.009	-0.009	-0.009	-0.008
R^2	0.61	0.71	0.69	0.71	0.55	0.65
Include baseline controls	y	y	y	y	y	y

Notes: N=235 in all columns. This table reports OLS estimates analogous to columns (1) and (2) in Table 2 for alternative samples of either non-college men or all prime-aged men and women, using the same set of baseline controls. See Table 2 for more details. The standardized effects rescale the coefficient by a one standard deviation change using the cross-MSA standard deviation. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 4
Non-Employment Response to Housing Demand Change and Manufacturing Decline: Longer Run Results

	Dependent Variable is Change in Non-Employment Rate					
Change defined across following years:	2000-2007		2000-2011		2000-2011	
Sample:	Non-College Men	All Men and Women	Non-College Men	All Men and Women	Non-College Men	All Men and Women
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Housing Demand Change, 2000-2007	-0.014	-0.010	-0.001	-0.001		
	(0.004)	(0.002)	(0.009)	(0.005)		
	[0.003]	[0.000]	[0.955]	[0.801]		
Predicted Manufacturing Decline, 2000-2007	-0.641	-0.665	-0.710	-0.726		
	(0.246)	(0.148)	(0.408)	(0.244)		
	[0.013]	[0.000]	[0.089]	[0.005]		
Predicted Housing Demand Change, 2000-2011					-0.038	-0.029
					(0.010)	(0.005)
					[0.001]	[0.000]
Predicted Manufacturing Decline, 2000-2011					-0.690	-0.575
					(0.298)	(0.171)
					[0.026]	[0.002]
Standardized (1σ) effects:						
Housing demand change	-0.011	-0.008	0.000	-0.001	-0.017	-0.013
Manufacturing decline	-0.007	-0.007	-0.007	-0.008	-0.014	-0.012
R^2	0.71	0.77	0.54	0.60	0.65	0.73
Include baseline controls	y	y	y	y	y	y

Notes: N=235 in all columns. This table reports OLS estimates analogous to columns (1) and (5) in Table 2 for alternative sample periods. See Table 2 for more details. In columns (1) through (4), the Predicted Manufacturing Decline variable is constructed across 2000-2007 time period, while in columns (5) and (6) it is constructed for the 2000-2011 period. The standardized effects rescale the coefficient by a one standard deviation change using the cross-MSA standard deviation. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 5

Wage and Population Response to Housing Demand Change and Manufacturing Decline

Change defined across following years:	2000-2007		2000-2011	
Sample:	Non-College Men	All Men and Women	Non-College Men	All Men and Women
	(1)	(2)	(3)	(4)
Panel A: Dependent Variable is Change in Average Wages				
Predicted Housing Demand Change, 2000-2007	0.030	0.023	0.026	0.026
	(0.005)	(0.004)	(0.010)	(0.006)
	[0.000]	[0.000]	[0.013]	[0.000]
Predicted Manufacturing Decline, 2000-2007	1.744	1.073	1.968	1.191
	(0.353)	(0.290)	(0.502)	(0.455)
	[0.000]	[0.001]	[0.000]	[0.012]
Standardized (1σ) effects:				
Housing demand change	0.023	0.018	0.020	0.020
Manufacturing decline	0.018	0.011	0.021	0.012
R^2	0.46	0.48	0.36	0.35
Panel B: Dependent Variable is Change in Population				
Predicted Housing Demand Change, 2000-2007	0.031	0.030	0.024	0.025
	(0.022)	(0.018)	(0.025)	(0.024)
	[0.164]	[0.098]	[0.341]	[0.304]
Predicted Manufacturing Decline, 2000-2007	2.188	1.956	3.793	2.979
	(0.850)	(0.775)	(1.024)	(0.988)
	[0.014]	[0.015]	[0.001]	[0.004]
Standardized (1σ) effects:				
Housing demand change	0.024	0.023	0.018	0.019
Manufacturing decline	0.023	0.021	0.040	0.031
R^2	0.17	0.18	0.26	0.18
Include baseline controls	y	y	y	y

Notes: N=235 in all columns. This table reports OLS estimates analogous to columns (1) through (4) in Table 4 for alternative dependent variables. See Table 4 for more details. In all columns, the Predicted Housing Demand Change and the Predicted Manufacturing Decline variables are constructed across 2000-2007 time period. The standardized effects rescale the coefficient by a one standard deviation change using the cross-MSA standard deviation. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 6
First Stage for Housing Demand Change Using
Magnitude of Structural Break in House Prices as Instrumental Variable

Dependent variable:	Predicted Housing Demand Change, 2000-2007		Change in Share of Non-College Men Employed in Manufacturing, 2000-2007
	(1)	(2)	(4)
Magnitude of Structural Break in House Prices	6.580	6.848	0.020
[Housing Boom Instrument]	(1.013)	(0.797)	(0.021)
	[0.000]	[0.000]	[0.348]
Predicted Manufacturing Decline		31.394	1.219
		(4.734)	(0.078)
		[0.000]	[0.000]
Standardized (1σ) effects:			
Change in housing demand instrument	0.379	0.394	0.001
Manufacturing decline		0.329	0.013
First-stage F-statistic	42.174	73.904	
R^2	0.52	0.67	0.52
Include baseline controls	y	y	y

Notes: N=235 in all columns. This table reports results of estimating equation (6) by OLS. The control variables included are initial (year 2000) values of the share of employed workers with a college degree, the share of women in labor force, and log population. The Magnitude of Structural Break in House Prices corresponds to the estimated MSA-specific magnitude of structural break in house price as estimated from 2000-2006 quarterly house price data (from FHFA), where the structural break is constrained to be between 2003-2005 (inclusive). The standardized effects rescale the coefficient by a one standard deviation change using the cross-MSA standard deviation. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 7

Non-Employment Response to Housing Demand Change and Manufacturing Decline: Instrumental Variable Estimates using Magnitude of Structral Break in House Prices

Dependent Variable is Change in Nonemployment Rate, 2000-2007

Sample:	Non-College Men	College Men	Non-College Women	College Women	All Men and Women
	(1)	(2)	(3)	(4)	(5)
Predicted Housing Demand Change	-0.018	-0.006	-0.007	0.001	-0.010
	(0.006)	(0.002)	(0.004)	(0.003)	(0.003)
	[0.004]	[0.005]	[0.111]	[0.769]	[0.002]
Predicted Manufacturing Decline	-0.698	-0.393	-0.859	-0.378	-0.706
	(0.228)	(0.120)	(0.155)	(0.164)	(0.134)
	[0.004]	[0.002]	[0.000]	[0.026]	[0.000]
Standardized (1σ) effects:					
Housing demand change	-0.014	-0.004	-0.005	0.001	-0.008
Manufacturing decline	-0.007	-0.004	-0.009	-0.004	-0.007
First stage F-statistic	73.90	64.64	74.91	64.86	72.90
N	235	235	235	235	235
R^2	0.71	0.22	0.69	0.13	0.77
Include baseline controls	y	y	y	y	y

Notes: N=235 in all columns. This table reports IV estimates analogous to columns (1) through (5) in Table 2 for alternative demographic groups using the same set of baseline controls. The Magnitude of Structural Break in House Prices is used as an instrument for Elasticity-Weighted House Price Change. See Table 2 and Table 6 for more details. The standardized effects rescale the coefficient by a one standard deviation change using the cross-MSA standard deviation. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 8
Displaced Manufacturing Workers and Housing Booms

Sample: Non-college Men, Age 18-64, Manufacturing Workers Displaced 1992-2005
Source: CPS Displaced Worker Surveys, 1994-2006

Dependent variable:	Non-Employment			Construction Employment		
	(1)	(2)	(3)	(4)	(5)	(6)
Difference-in-difference estimate of effect of housing boom:						
Displaced between 1996 and 2005 ×	-0.101	-0.115	-0.111	0.011	0.035	0.038
Housing Boom MSA	(0.043)	(0.047)	(0.047)	(0.014)	(0.013)	(0.012)
	[0.025]	[0.019]	[0.023]	[0.442]	[0.009]	[0.003]
Difference-in-difference controls:						
Displaced between 1996 and 2005	0.013			0.021		
	(0.021)			(0.009)		
	[0.544]			[0.018]		
Housing Boom MSA	0.077			-0.016		
	(0.044)			(0.011)		
	[0.090]			[0.171]		
Mean of dependent variable	0.326	0.326	0.326	0.056	0.056	0.056
N	3051	3051	3051	3051	3051	3051
R^2	0.00	0.12	0.14	0.00	0.09	0.10
Include MSA fixed effects		y	y		y	y
Include Displacement Year fixed effects		y	y		y	y
Include Individual-level controls			y			y

Notes: This table reports OLS estimates of equation (10). The first row reports the Difference-in-Difference estimate of the effect of being displaced during housing boom time period within an MSA that was experiencing a housing boom. An MSA is defined to be a "Housing Boom MSA" if it has an above-mean value of the instrumental variable used in Tables 6 and 7, otherwise (if a displaced worker is not in one of these MSAs or is in a non-metro region) this indicator is set to 0. The controls in columns (3) and (6) are the following: education, union status in last job, and 5th-degree polynomial in age. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 9
Model Predictions of the Effect of Housing Demand Change and Manufacturing Decline on National Trends in Non-Employment

	Actual Change (1)	Predicted Change due to Housing Demand Change (2)	Predicted Change due to Manufacturing Decline (3)	Residual Change, (1) - (2) - (3) (4)	Share of Actual Change Explained by Manufacturing + Housing (5)
Panel A: Accounting for National Non-Employment Trends for All Men and Women					
2000-2007	0.019	-0.009	0.021	0.007	65.3%
2000-2011	0.073	0.000	0.032	0.041	43.7%
Panel B: Accounting for National Non-Employment Trends for Non-College Men					
2000-2007	0.022	-0.012	0.031	0.004	83.3%
2000-2011	0.108	0.000	0.046	0.062	42.1%
Panel C: Accounting for National Non-participation Trends for Non-College Men					
2000-2007	0.013	-0.006	0.014	0.005	61.6%
2000-2011	0.046	0.000	0.021	0.025	45.7%
Panel D: Accounting for National Unemployment Trends for Non-College Men					
2000-2007	0.011	-0.008	0.017	0.003	77.9%
2000-2011	0.076	0.000	0.025	0.051	32.8%

Notes: This table reports counterfactual estimates of predicted changes in aggregate non-employment for different demographic groups. The coefficient estimates from Table 2 and Table 5 are used to compute the predicted values. Actual changes in non-employment, housing prices, and manufacturing employment are taken from the CPS.

Figure 1a: Trends in Employment in Manufacturing and Construction for Non-College Men, 1974-2011

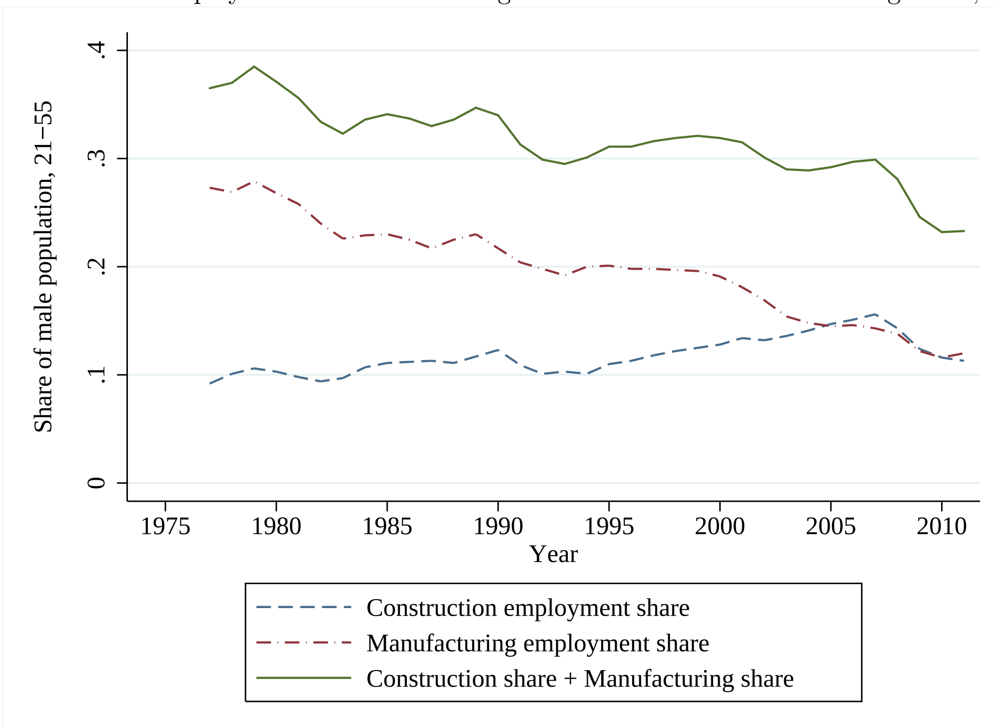
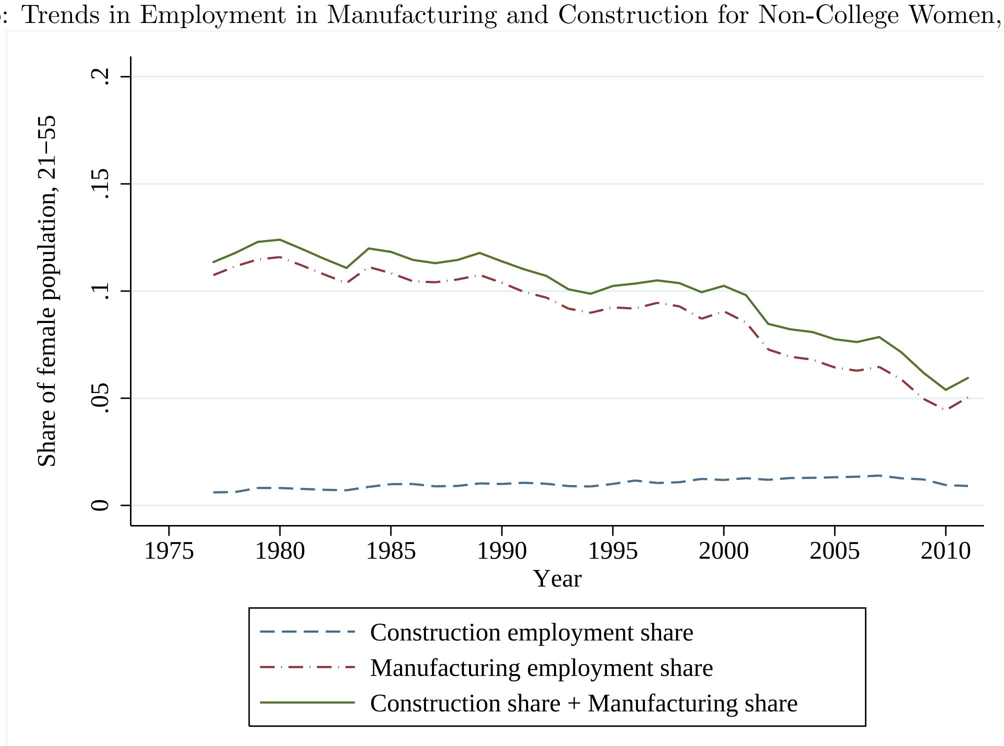


Figure 1b: Trends in Employment in Manufacturing and Construction for Non-College Women, 1974-2011

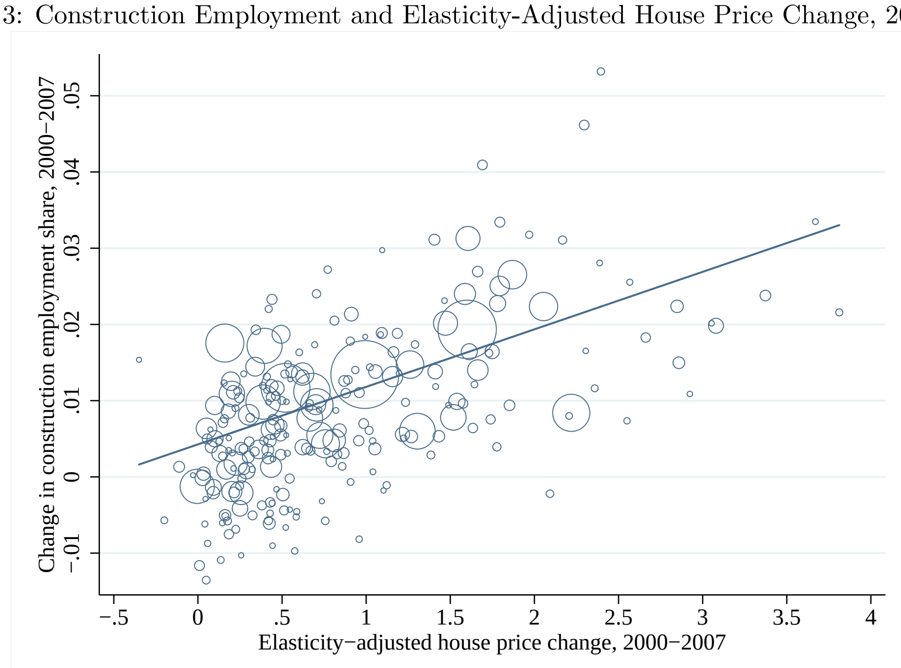


<u>Notes:</u> These figures use data from the March CPS. The sample includes all non-institutionalized men/women without a college degree, age 21-55.

Figure 2: Predicted Manufacturing Decline and Manufacturing Employment, 2000-2007

Notes: This figure reports the correlation across cities between the predicted change in manufacturing employment and changes in manufacturing employment between 2000 and 2007. The manufacturing decline variable is constructed following Bartik (1991); see Data Appendix for details. The change in manufacturing employment is defined as the change in the share of the total population of men and women age 21-55 employed in manufacturing. Each circle represents a metropolitan area, and the size of the circle is proportional to the prime-age population in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

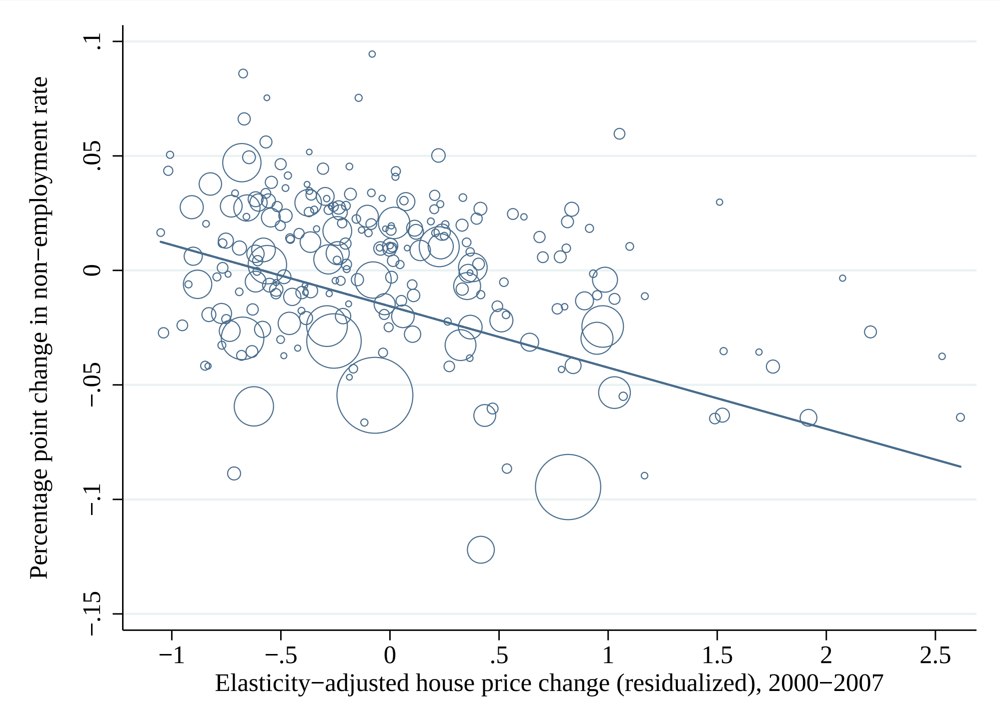
Figure 3: Construction Employment and Elasticity-Adjusted House Price Change, 2000-2007



Notes: This figure reports correlation across cities between the 2000-2007 change in share of population employed in construction and the change in housing prices over the same time period. Each circle represents a metropolitan area, and the size of the circle is proportional to the number of prime-age men and women in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

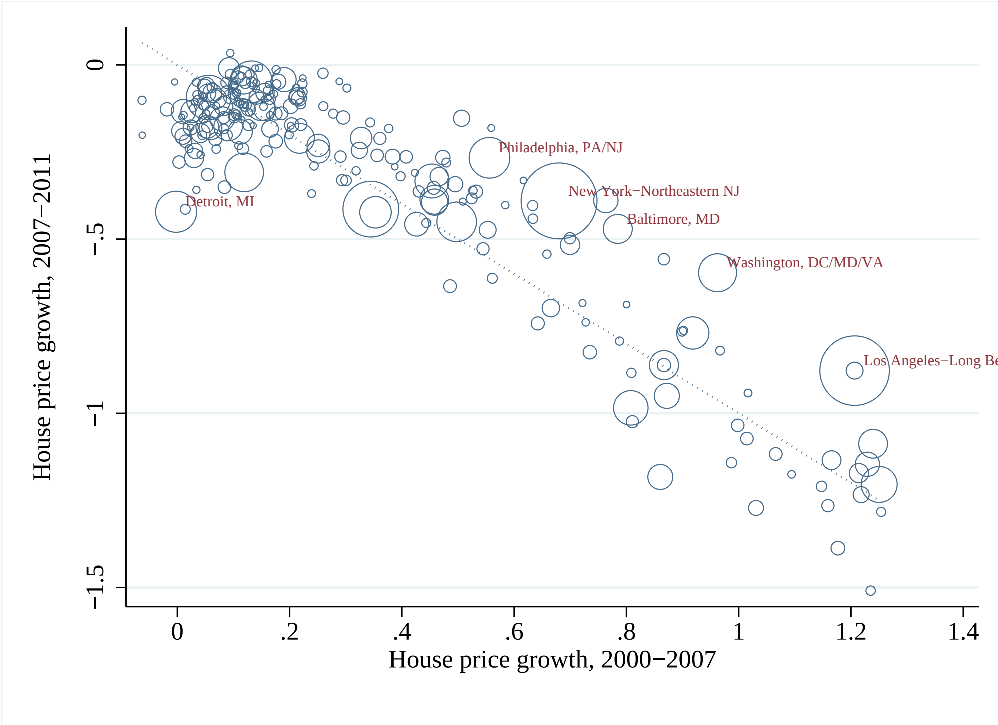
Figure 4a: Correlation Between Manufacturing Decline Proxy and Change in Non-Employment Rate of Non-College Men, 2000-2007

Figure 4b: Correlation Between (Residualized) Elasticity-adjusted House Price Change and Change in Non-Employment Rate of Non-College Men, 2000-2007



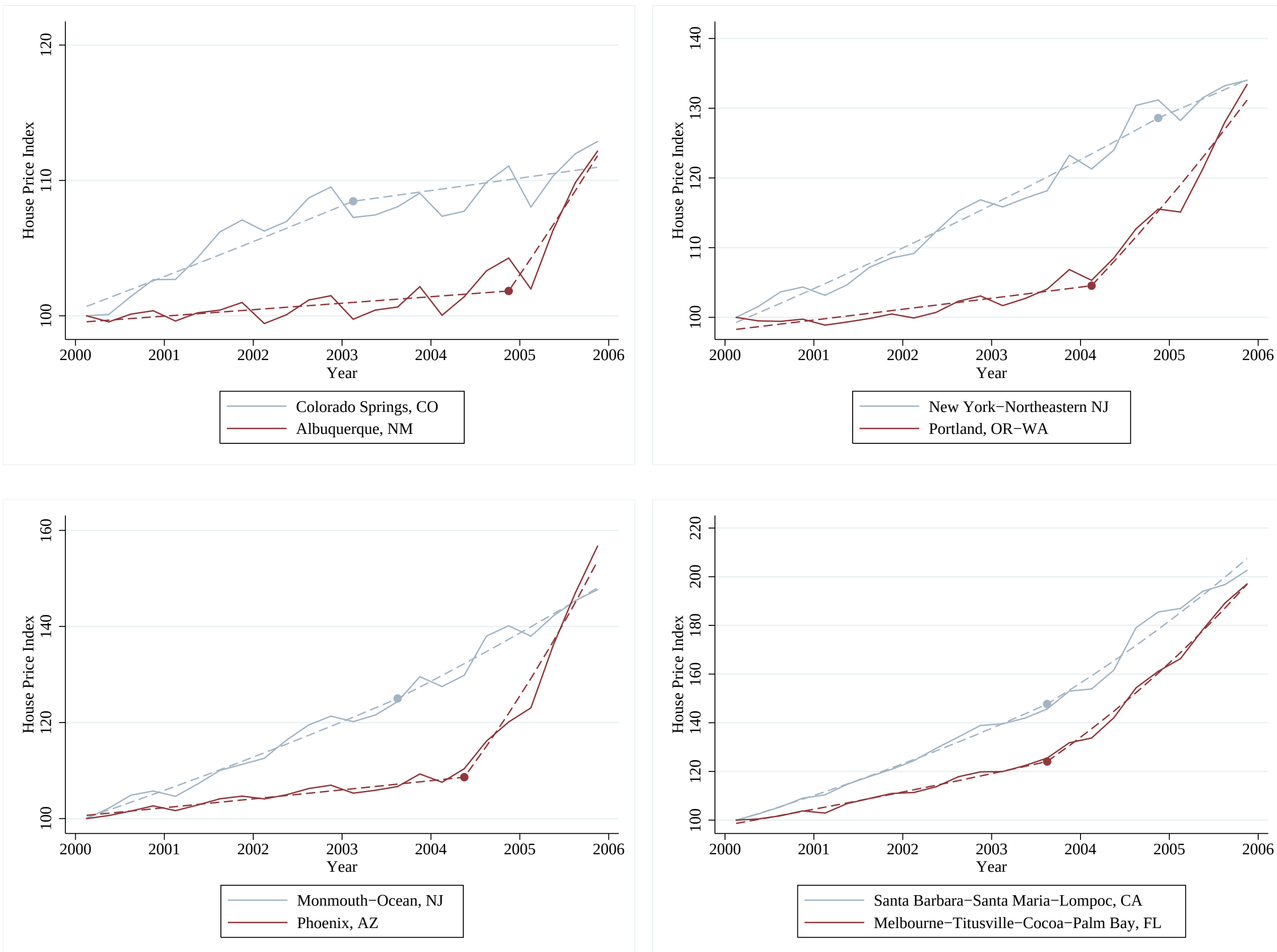
Notes: These figures show correlation between the change in non-employment rate of non-college men and both the proxies for change in manufacturing labor demand and change in housing demand. In Figure 4b, the manufacturing labor demand proxy is first residualized out of the housing demand proxy (elasticity-adjusted house price change). This is intended to mimic the two-step empirical model estimated in the tables below, where we allow manufacturing shocks to have a direct effect on housing demand.

Figure 5: House Price Growth, 2007-2011 versus 2000-2007



Notes: These figure shows the correlation between the change in house prices in 2000-2007 and the change in house prices in 2007-2011 for the 235 MSAs in our baseline sample. The dotted line is a 45-degree line (i.e., slope of -1). Cities are labelled if they are one of the largest 30 MSAs in sample are are more than 25 percentage points (vertically) from the 45-degree line.

Figure 6: Variation in Magnitude of Structural Break Across Cities with Similar Price Growth



Notes: This figre shows graphs of quarterly (residualized) house price data for 8 MSAs. The (residualized) house price index for each city is normalized so that 2000 Q1 is 100. The FHFA quarterly house price data is regressed on a cubic time polynomial in the predicted manufacturing decline variable and the other baseline controls described in Table 1 to produce the residualized house prices. The solid and dashed lines report the residualized house price series while the doted lines reports the structural break estimates, with a solid dot indicating the estimated quarter of the structural break. The 8 MSAs are grouped by overall (residualized) house price growth, but differ in magnitude of estimated structural break.

Figure 7: Graphical Solutions of Sectoral Choice Model

Figure 7a: Initial Equilibrium

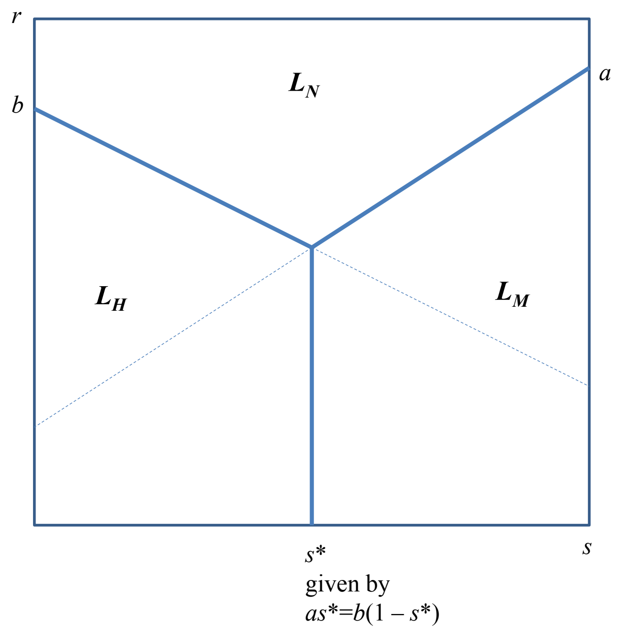
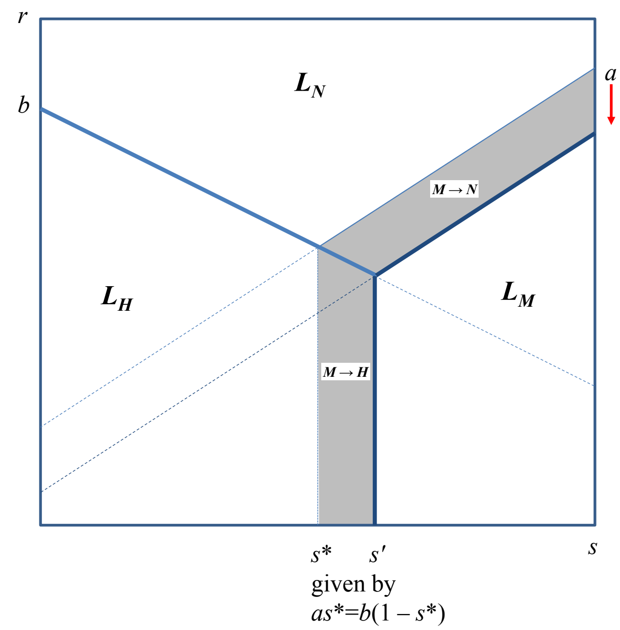
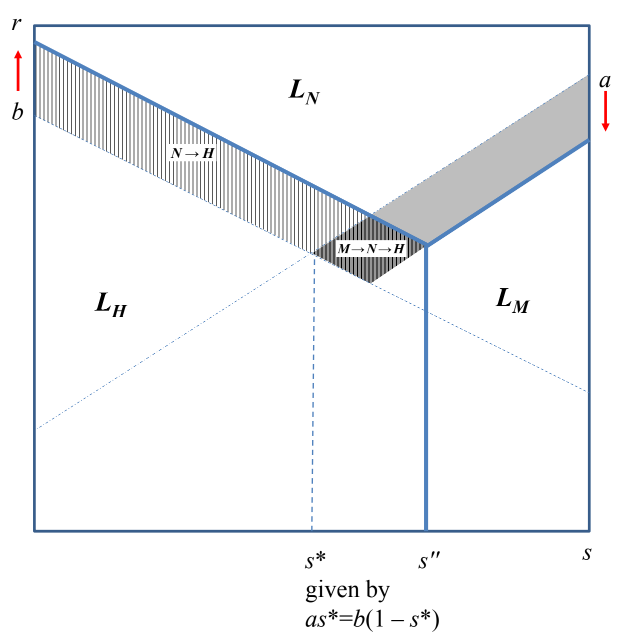
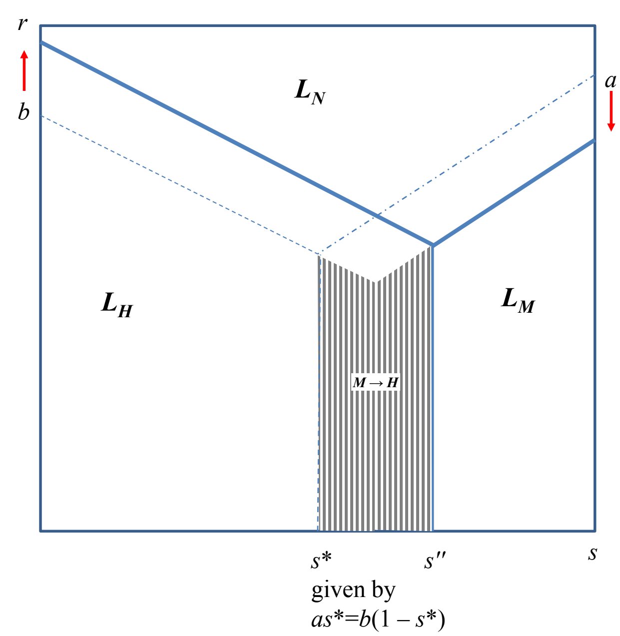


Figure 7b: Negative Shock to Sector M



Figures 7c and 7d: Negative Shock to Sector M and “Offsetting” Positive Shock to Sector H

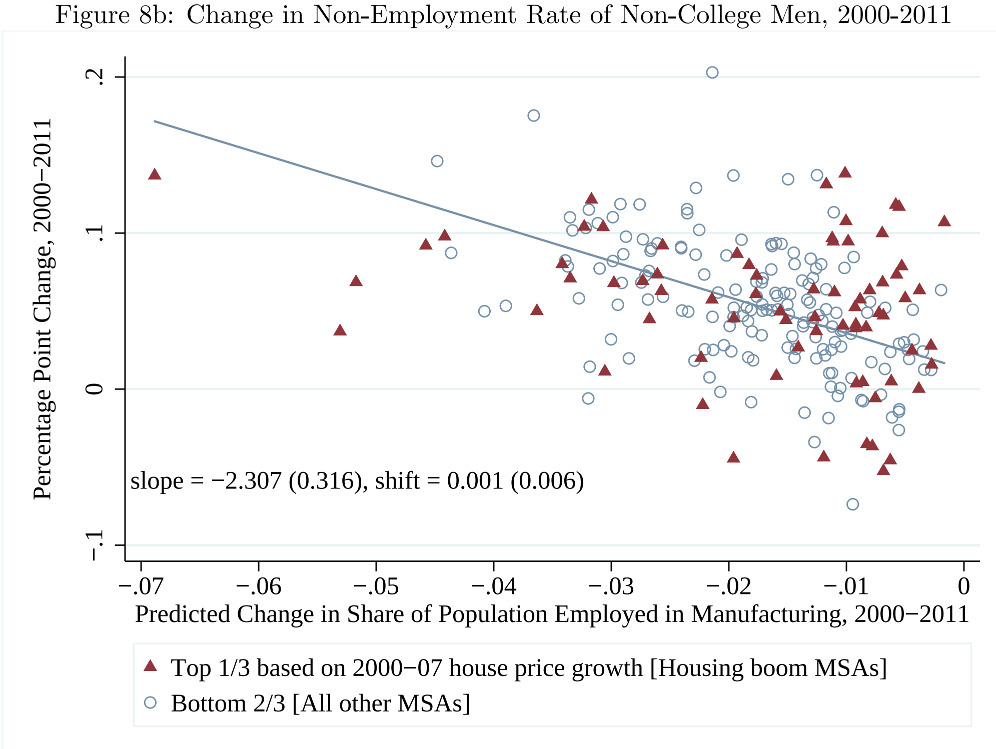




Notes: These figures show the graphic solutions of the model. In Figure 7a, we show the initial equilibrium, which shows the combination of s and r) parameters determine how workers self-select into sectors (or into non-employment, N). Figure 7b shows how the equilibrium responds to a negative shock to sector M; workers leave sector M for either sector H or enter non-employment (sector N), with the relative importance of these two channels depending on the mass of workers along each margin. Lastly, Figures 7c and 7d shows how the equilibrium responds an “offsetting” positive shock to sector H. In this case, some workers who would have entered non-employment in Figure 7b instead remain employed and enter sector H (center diamond in Figure 7c).

Figure 8a: Change in Non-Employment Rate of Non-College Men, 2000-2007

Figure 8b: Change in Non-Employment Rate of Non-College Men, 2000-2011



Notes: These figures report the correlation across cities between the predicted change in manufacturing employment and the change in the non-employment rate of non-college men (age 21-55) between 2000-2007 and 2000-2011. The manufacturing decline variable and dependent variables are constructed using data from the 2000 Census, the 2005-2007 ACS, and the 2009-2011 ACS; see the notes to Figure 2 and the Data Appendix for more details. The sample is divided based on the (residualized) elasticity-weighted house price change in the metropolitan area between 2000 and 2007, where the local manufacturing variable has been residualized out of the change in (elasticity-weighted) house prices. The bottom two-thirds of the metropolitan areas based on the residualized elasticity-weighted house price change are shown in light-colored circles; the top one-third are shown in dark-colored triangles. The solid line represents the weighted OLS regression line that is computed based on the bottom two-thirds sample.

Figure 9a: Displaced Manufacturing Workers, Housing Booms, and Non-employment

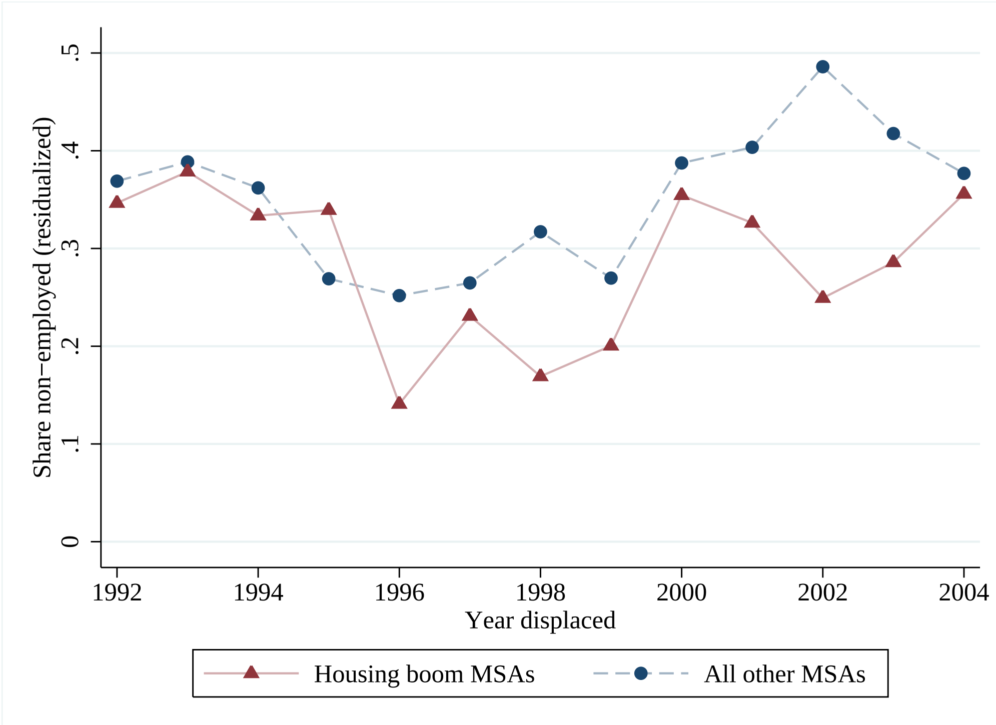
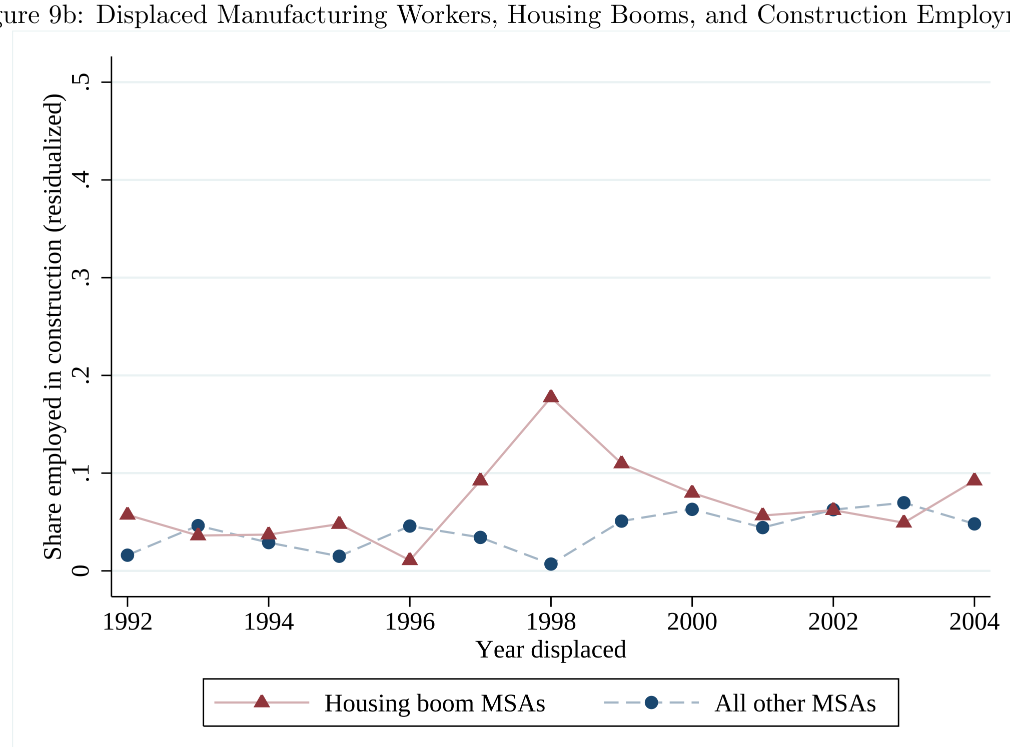


Figure 9b: Displaced Manufacturing Workers, Housing Booms, and Construction Employment



Notes: The figures above report the (residualized) share of displaced male manufacturing workers aged 18-64 who are in non-employment and the share employed in construction across two sub-samples: (1) workers who were displaced in MSAs that experienced a "housing boom" as defined in Figures 5 through 8 and (2) workers who were displaced in other MSAs or were displaced in non-metro areas. All data come from CPS Displaced Worker Survey, 1994-2006. The residualized share is created by residualizing indicator variables for difference (in years) between the year of displacement and the (calendar) year of the survey as well as MSA fixed effects.